View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Helsingin yliopiston digitaalinen arkisto

Does honesty pay back? Using a dynamic algorithm in rebating – the role of information, fairness and affects in behavioral intentions outcomes

Dmitry Poletaev
Master's Thesis
Psychology
March 2017
Supervisors: Petri Parvinen &
Marko Elovainio

HELSINGIN YLIOPISTO – HELSINGFORS UNIVERSITET – UNIVERSITY OF HELSINKI

Tiedekunta – Fakultet – Faculty	Laitos – Institution – Department
Lääketieteellinen tiedekunta	**Psykologian ja logopedian osasto**

Tekijä – Författare – Author

Poletaev, Dmitry

Työn nimi – Arbetets titel – Title

Kannattaako rehellisyys? Dynaamisen algoritmin käyttö hyvityksissä – tiedon, oikeudenmukaisuuden ja affektien vaikutus käyttäytymisintentioihin

Oppiaine – Läroämne – Subject

Psykologia

Työn ohjaaja(t) – Arbetets handledare – Supervisor	Vuosi – År – Year
Parvinen, Petri (Aalto yliopisto, Tuotantotalouden laitos), Elovainio, Marko (HY, Psykologia)	**2017**

Tiivistelmä – Abstrakt – Abstract

Tavoitteet. Tässä tutkimuksessa tarkoituksena oli selvittää, miten ei-tunnistavan dynaamisen algoritmin käyttö ostohyvityksen kontekstissa vaikuttaa oikeudenmukaisuuden kokemukseen ja sitä kautta käyttäytymisaikomuksiin. Tämän lisäksi, selvitettiin, miten yksityiskohtaisemman tiedon tarjoaminen algoritmin toiminnasta vaikuttaa oikeudenmukaisuuden kokemukseen. Dynaamisen hinnoittelun, erityisesti tunnistuspohjaisen, on osoitettu aiemmin vaikuttavan negatiivisesti oikeudenmukaisuuteen. Dynaamiset algoritmit ovat tuottavuudeltaan parempia yrityksille, ja siksi reunaehtojen selvittäminen; miten niitä voi ottaa käyttöön kunnioittaen kuluttajissa herättämiä reaktioita, on tärkeää. Eritasoinen entiteetti-/tapahtumaoikeudenmukaisuuden tutkiminen oikeudenmukaisuuden heuristiikkateoriasta käsin oli valittu tämän tutkimuksen selkärangaksi laajentamaan mosaiikkimaista empiiristä näyttöä niiden keskinäisistä vuorovaikutuspoluista. Oikeudenmukaisuuden kokemus on myös tiiviissä yhteydessä tunteisiin, sekä satunnaisten affektien että itse oikeudenmukaisuuden kokemuksen herättämien integraaliemootioiden osalta. Tämän takia näiden tarkastelu oli sisällytetty tähän tutkimukseen täydentämään kokonaiskuvaa.

Menetelmät. Tutkimuksessa manipulaatiot suoritettiin kahdessa tasossa. Ensimmäinen taso, dynaamiselle algoritmille altistuminen tai ihmisen asettamien hyvitysprosenttien näkeminen tapahtui yrityksen järjestelmässä algoritmin kokeilun yhteydessä. Toinen manipulaation taso, tiedon määrä, tehtiin kyselyaineiston keräämisen yhteydessä. Tiedon määrässä oli kolme ryhmää: ei mitään tietoa (kontrolli), pelkkä tieto meneillään olevasta kokeilusta sekä tieto meneillään olevasta kokeilusta sisältäen tiedon algoritmin toiminnasta. Lopullisissa analyyseissä käytetyn aineiston koko oli 404. Pääasiallinen käytetty analyysimenetelmä oli rakenneyhtälömallinnus.

Tulokset ja johtopäätökset. Vaikutuspolut tapahtuma- ja entiteettioikeudenmukaisuuksien välillä olivat oikeudenmukaisuuden heuristiikkateorian mukaisia - tapahtumaoikeudenmukaisuus medioi osittain entiteettioikeudenmukaisuuden muutosta. Algoritmille altistuneilla ainoastaan meneillään olevasta kokeilusta tarjotulla informaatiolla oli odotettua negatiivista vaikutusta koettuun tapahtumaoikeudenmukaisuuteen. Lisätiedon tarjoamisella ei ollut vaikutusta oikeudenmukaisuuteen. Entiteettioikeudenmukaisuus oli yhteydessä sekä satunnaisiin affekteihin, että integraaliemootioihin. Vastaavaa yhteyttä affektien ja emootioiden sekä tapahtumaoikeudenmukaisuuden välillä ei ollut. Oikeudenmukaisuus medioi vain osittain muutosta satunnaisten affektien ja integraaliemootioiden välillä. Integraaliemootiot eivät olleet yhteydessä käyttäytymisaikomuksiin. Entiteettioikeudenmukaisuus medioi täysin tapahtumaoikeudenmukaisuuden vaikutuksen käyttäytymisaikomuksiin. Lisätiedon tarjoaminen vaikutti suoraan positiivisesti pro-aktiivisiin käyttäytymisaikomuksiin ilman oikeudenmukaisuuden mediointia. Mitään manipulaatioiden suoria vaikutuksia valittamisaikomuksiin ei ilmennyt. Tulokset antavat tärkeää tietoa dynaamiselle algoritmille altistamisen vaikutuksista tosielämässä, laboratorioiden ulkopuolella. Vaikka dynaaminen hinnoittelu koetaan lähtökohtaisesti epäoikeudenmukaiseksi, algoritmin toiminnan periaatteiden kertomisella voi olla positiivisia vaikutuksia lopputuloksiin. Tunteiden vaikutuksesta on hinnoitteluoikeudenmukaisuuden kontekstissa saatu vain rajallista tukea.

Avainsanat – Nyckelord – Keywords

Dynaaminen hinnoittelu, ostohyvitys, oikeudenmukaisuus, diskreetit affektit, rakenneyhtälömallinnus, psykologia

Säilytyspaikka – Förvaringsställe – Where deposited

Helsingin yliopiston kirjasto – Helda / E-thesis (opinnäytteet) *ethesis.helsinki.fi*

HELSINGIN YLIOPISTO – HELSINGFORS UNIVERSITET – UNIVERSITY OF HELSINKI

Tiedekunta – Fakultet – Faculty	Laitos – Institution – Department
Faculty of Medicine	**Department of Psychology and logopedics**

Tekijä – Författare – Author

Poletaev, Dmitry

Työn nimi – Arbetets titel – Title

Does honesty pay back? Using a dynamic algorithm in rebating – the role of information, fairness and affects in behavioral intentions outcomes

Oppiaine – Läroämne – Subject

Psychology

Työn ohjaaja(t) – Arbetets handledare – Supervisor	Vuosi – År – Year
Parvinen, Petri (Aalto University, Department of Industrial Engineering and Management), Elovainio, Marko (HU, Psychology)	**2017**

Tiivistelmä – Abstrakt – Abstract

Goals. The goal of this research was to find out, how the use of the non-identifying dynamic algorithm would affect fairness experience; and through it, behavioral intentions, in rebating context. Besides that, it was assessed how the provision of detailed information on algorithm's logic affects the fairness experience. Dynamic pricing, especially based on identification, has been shown to negatively affect fairness. The dynamic algorithms are better to companies due to their profitability potential. It is of vital importance to find out the conditions, on which they might be employed, while taking into account the possible reactions of the customers. A differential assessment of entity and event fairness through the lens of fairness heuristic theory is chosen as a backbone of this research to extend the mosaic empirical evidence of their mutual interaction paths. The fairness experience is also closely connected to affects; incidental affects and integral emotions, which are evoked by the fairness experience itself. Because of this close relationship, to complement general picture, the affects were assessed as well.

Methods. The manipulations were performed on two levels. The first level, the exposure to dynamic algorithm or seeing the human-set pre-determined rebate rates, happened on the company's site when the algorithm trial was run. The second manipulation level, the amount of the available information, was performed during the gathering of the survey data. There were three conditions in the information manipulation: no information (the control), bare information about the ongoing trial and trial information including a detailed algorithm's logic description. The size of the final sample, used for the analysis, consisted of 404 participants. The main analysing technique employed was SEM.

Results and conclusions. Effect paths between entity and event fairness areas were in accordance with the fairness heuristic theory - event fairness mediated the change in entity fairness partially. The subjects that were exposed to the algorithm, event fairness was affected negatively by the bare trial information as expected. The provision of the detailed information did not affect fairness. Entity fairness was connected to both, incidental affects and integral emotions. There were no analogous connection between event fairness, and affects and emotions. Fairness mediated only partially the change from incidental affects to integral emotions. Integral emotions were not connected to the behavioral intentions. Entity fairness mediated fully the effect of event fairness on the behavioral intentions. The provision of the detailed information affected directly positively on pro-active behavioral intentions without a mediation of fairness. None of the manipulations affected directly complaining intentions. The results provide important information about the dynamic algorithm exposure in real life, outside the laboratories. Despite the dynamic pricing being seen as unfair in principle, the exposure to the detailed information might have positive effects on the outcomes. There was only a limited support for the role of affects in the pricing fairness context.

Avainsanat – Nyckelord – Keywords

Dynamic pricing, rebate, fairness, discrete affects, SEM, psychology

Säilytyspaikka – Förvaringsställe – Where deposited

Helsingin yliopiston kirjasto – Helda / E-thesis (opinnäytteet) *ethesis.helsinki.fi*

Contents

1. Introduction

Dynamic approach to pricing, also called price discrimination or differentiation, is an often used mean in yield management to maximize profits and to optimize demand load (Kimes, 1994). There are plural examples. Hotels are known for adjusting their prices based on season, having rooms priced lower during low season and higher during high season. Airlines adjust their prices based on the reservation situation, thus tickets bought with a shorter notice cost generally more. There are also other kinds of examples. For instance, Coca-Cola experimented with weather-based dynamic pricing in vending machines, where drinks were cheaper on cloudy days and more expensive on sunny days (King & Narayandas, 2000 via Lee, Illia, & Lawson-Body, 2011). Amazon.com tried dynamic pricing based on customers' purchase history, and loyal customers were given a higher price for the same product than other customers (Cox, 2001). Each of these examples represent the logic of dynamic pricing, but on different grounds. The pricing practices of hotels and airlines are generally accepted by the public, yet Amazon.com and Coca-Cola's experiments unleashed severe negative reactions among customers. Where is the difference?

The key element to understand those reactions is the differential fairness experience between the settings. Some bases for dynamic pricing are acceptable by customers, when the others are not. Fairness theories provide insight into this. According to distributional justice perspective, if the price change is not a result of change in entity's effort – it is usually seen as unfair. Dynamic pricing, when price changes independently from company's efforts, is interpreted generally as unacceptable within this framework. Airlines and hotels, as they have a limited supply, are therefore seen as more entitled to price changes based on demand, than retail shops without same kind of supply restrictions.

In new areas, where dynamic pricing has not been a general practice, the companies might hesitate employing the dynamic pricing, despite the availability of technological means for its implementation, especially due to the possibility of customers' uproar. In theory, companies could conceal the use of dynamic pricing, by refraining from the disclosure of relevant information and by tailoring the price relevant information individually. But, as seen in the Amazon.com case, this kind of information doesn't stay private for long in the Internet era, and after Amazon.com's customers got wind of it the uproar was unavoidable.

If the dynamic pricing is employed, the next question is what kind of technique to use. Between the different dynamic pricing techniques, the ones using auction based approach tend to be perceived as less unfair (Haws & Bearden, 2006). When the price is given by the seller, the dynamic pricing techniques that employ buyer identifications are seen as more unfair (Grewal, Hardesty & Iyer, 2004). The problem of those researches is that they are vignette based experiments, and thus not giving full ecological validity. Another problem is that those researches assess cognitive appraisals, thus not considering affectivity, nor other areas of the human mind.

Taking everything together, what will happen when this dynamic pricing algorithm, which does not identify customers, is tested outside of the laboratory? What if customers are explicitly told about it being used? These are the questions this study tries to answer. The trial of group level price optimization algorithm is carried out in rebating contexts with survey-based manipulation of available information about the trial. To control the situation independent variables, the incidental affects and the personality are assessed as well.

1.1. Rebating

A rebate is usually a promotion scheme done by a product manufacturer, where a certain amount of paid price is reimbursed straightly to the consumer after the consumer mailed back a check or other evidence of the purchase. The tool is not new, and is known from the 80s (Brown, 1999). It is known that the lion’s share of the consumers, who buy rebate-promoted goods, fail to redeem the mail-in rebates – phenomenon known as “slippage” (Lu & Moorthy, 2007). Thus there is interest to identify the consumers’ proneness to rebating (McCall, Bruneau, Ellis & Mian, 2009); to understand how the subjective estimation of the redemption likelihood and motivation affects the “slippage” phenomenon (Gourville & Soman, 2011); to assess the effect of rebate promotion presentation style on purchase (Kim, 2006); to compare the rebate and matching promotion schemes’ differences on a purchase (Davis & Millner, 2005); and to compare a rebate promotion within different product categories (Coker, Pillai, & Balasubramanian, 2010). There is also more cognitive oriented series of experimental studies assessing difference between a mail-in and an instant rebate; the willingness to pay for the immediate or delayed outcomes, and the effect of positive affect (Pyone & Isen, 2011).

However, there is a derivative rebating scheme where a third company autonomously provides rebates on-behalf of several other companies providing different services. This can happen either via card usage or online. In this procedure the registration of the rebate is automatic, thus ruling out the possibility of a redemption fail for the customer. This type of a rebate can be seen as some type of a bonus/loyalty card. There is no relevant behavioral research, that the author is aware of, which assesses the third-party bonus/loyalty card use per se, albeit some research has been done in the traditional bonus card field, which is presented next.

On behalf of the company, there are strong incentives for the use of the loyalty cards. Most importantly, the information gathered via use of the loyalty cards provides significant information about consumer behaviour for shops (Cortiñas, Elorz & Múgica, 2008). Also, it is shown in an international comparative study that the loyalty cards have behavioral and attitudinal impact when there are fewer alternative options and customers have not become accustomed to the cards (Noordhoff, Pauwels & Odekerken-Schröder, 2004).

The bonus/loyalty cards are, on the other hand, a part of a larger paradigm - loyalty programs (for review: Dorotic, Bijmolt & Verhoef 2012). The goal of the loyalty programs is to increase loyalty and spending of the customers. Though there is an increase in the loyalty programs' popularity, their effect is not straight-forward (Dorotic, Bijmolt &Verhoef, 2012; Liu, 2007). It is argued, that the loyalty programs are not alone responsible for the loyal behavior of the customers, but companies should take measures to teach the customers to use their loyalty programs (Frisou & Yildiz, 2011). The loyalty programs are sometimes build upon differentiative tiers (for instance a frequent flyer -status), which in turn have an effect on customer's perception of status (Dreze & Nunes, 2007), yet there is suggestive evidence that effect is industry specific (Arbore & Estes, 2013). It is also shown that frequency-based programs in retail can induce "cherry picking" behaviour, but elimination of this behaviour wouldn't be profitable (Lal & Bell, 2003).

When the internet is involved in rebating, especially when it is done by a third party, there is an incentive to poke the rates, to extract available surplus. Technically it is possible to automate adjustment of rebating rates based on the user response thus introducing dynamicity into the process. The closest relative available for rebates' dynamicity effects assessment is dynamic pricing, which is reviewed next.

1.2. Dynamic pricing

Kannan and Kopalle (2001) stated already 15 years ago that "[...] products and services sold over the Internet channel is becoming ever more dynamic". The definition of dynamic varies, but usually it means that price may vary between consumers (individual level price discrimination), across different times (different campaigns), or across different bundles of products or services (Kannan & Kopalle, 2001). This shift was possible mainly due to maturing technology as well as larger accumulation and processing of the customer data (Elmaghraby & Keskinocak, 2003). Though dynamic pricing has been known for a longer time in industries where the product capacity is limited, short-lived and transient; such as hotels, airlines and electric utilities, it's adoption to retailing etc industries with no such capacity problems is relatively newer trend (Elmaghraby & Keskinocak, 2003).

The dynamic pricing schemes may be divided into two large sub-classes: posted-price mechanisms and price-discovery mechanisms. The posted-price mechanisms meaning price setting as is, i.e. when the price is proposed to the customer, it can only be agreed or disagreed upon, leading to purchase when agreed. Price-discovery mechanisms are a way of finding a price level corresponding to wishes of both parties in a process of bidding or auction (Elmaghraby & Keskinocak, 2003).

However, the dynamic pricing is not totally free of troubles. As seen in a review of Amazon's differential pricing trial in 2000 by Cox (2001), dynamicity did not please customers. On the contrary, it was met with extreme displeasure and outrage forcing the company to cancel the trial. Cox (2001) proposed that "understanding of distributive and procedural justice, as well as equity theory and dual entitlement" would lead to better managerial solutions in the context of dynamic pricing. Besides that, Garbarino and Lee (2003) showed that individual level price discrimination leads to decreased trust in company. A more detailed review of the fairness research is presented in the next chapter.

1.3. Fairness

It is suggested that fairness has strong evolutionary roots, varying in examples of animal kingdom from positive effects of fair play in wolves' puppies to moralistic aggressions in monkeys (Brosnan, 2006). Thus it is not a surprise that the experience of fairness is one of the strongest components of social life in humans as well. Fairness is an age-old ground for philosophical inquiries. The roots of modern research go back all the way to Antique Greece and Aristotle's Nicomachean Ethics. Nevertheless, more precise empirical research on implications of fairness and their outcomes are dated within the past half-century (e.g. Adams, 1965).

Fairness is shown to be a major predictor in the behavioral reactions in different contexts. For instance in large meta-analysis of justice in organizational context by Colquitt et al. (2013), the fairness experience showed to have an effect on task performance, organizational citizenship behavior and counterproductive work behavior. In the price fairness area, the fairness experience has shown to have an effect on satisfaction (Herrmann, Xia, Monroe & Huber, 2007), shopping intentions (Campbell, 1999) and the actual loyalty (Chebat & Slusarczyk, 2005).

The fact that fairness and justice are often used interchangeably in the empirical research is noteworthy, albeit Goldman and Cropanzano (2015) express worry about concept imprecision. Therefore, to emphasize the subjective and evaluative nature of the experience, fairness term is used in this thesis as Goldman and Cropanzano (2015) put it: "[...] 'fairness' denotes evaluative judgment as to whether [morally required] conduct is morally praiseworthy"; while justice term shall be used to refer to "[…] whether one adheres to certain rules or standards […]".

1.3.1. Fairness heuristic theory

There are several approaches on how the fairness evaluations are formed; attributions, expectations and referent standards to name a few (Cropanzano, Stein & Nadisic, 2011, pp. 3). In this thesis fairness heuristic theory (FHT) (Lind, 2001) is adopted to form the central part of the general framework. The key proposition of FHT is that people use the heuristic approach to appraisal of fairness as a proxy for interpersonal trust and a shortcut for heavy and slow systematic cognitive appraisals, when it comes to decisions of cooperative behavior in day-to-day social situations (Lind, 2001, pp. 56).

The rooting of FHT is in so called *fundamental social dilemma*. By cooperating and providing personal effort and the resources to a social entity, group or organization, an individual can achieve better outcomes, increase capacity to achieve goals and give a broader social meaning by securing self-identity. On the other hand, such cooperation can be limitative for individual freedom and thus give a road for exploitation, not to mention exclusion or rejection by the social entity, thus leading to a loss of identity. Therefore FHT makes an assumption of the individual's two main sources of concern in the fundamental social dilemma - resource investment and identity. (Lind, 2001, pp. 61–63).

To resolve the fundamental social dilemma, individuals use imprecise fairness heuristic in decision-making to "switch" their own cooperation mode towards the social entity between an immediate self-interested "individual mode" and a pro-entity "group mode". This heuristic allows to save cognitive capacity, since the calculation of all possible cooperation outcomes would be a task too heavy to do repeatedly at each encounter. On the other hand, the using of the fairness heuristic provides also confidence to action, since once achieved, it gives systematic response toward certain social entity over different encounters. (Lind, 2001, pp. 65–67).

Lind (2001) defines FHT having two stages - a *judgemental phase* and a *use phase*. The judgemental phase, as name suggests, is when the fairness heuristic is formed; either in encountering a new social entity and trying to figure out which mode should be employed, or when there is a high uncertainty in the existing relationship, for instance if a serious change in the behavior of the social entity appeared, i.e. so called phase-shifting events. Characteristical to this phase is justice-related information gathering and processing. The use phase is literally when the formed fairness heuristic is used. It is used for the approximation of lacking justice related information, trust, compliance with entity rules, pro-social behavior and self-identification.

Lind (2001) also postulates the two main effects in FHT episodic pattern. Since the judgemental phase is brief and heuristic forming is done hurriedly, the first existing fairness-relevant information has the higher impact on the formed heuristic. This is called a *primacy effect*. On the other hand, the *substitutability effect* suggests whether there is a lack of information on some of the fairness areas during the judgemental phase, at which time it will be substituted via heuristic in the use phase.

1.3.2. The distinction of event and social entity fairness research paradigms

The fairness research can be divided into two separate paradigms – to an event paradigm and to a social entity paradigm. The former being mainly an experimental vignette-based research done in laboratories measuring fairness appraisals in reactions to certain events, while the latter consists mainly of correlational studies in the field seeking for connections between the different entity appraisals (e.g. organization's or supervisor's fairness) and the outcome variables. The core distinction of the paradigms rests on the difference between what someone *does* (e.g., an organization that behaved unfairly during downsizing) and what someone *is* (e.g., a fundamentally unfair organization) (Cropanzano, Byrne, Bobocel & Rupp, 2001).

Cropanzano et al. (2001) suggests that the main causal path would be seen going from an appraisal of events to form an appraisal of social entity fairness. However, they continue: "in the absence of other evidence, it seems reasonable to suppose that these paths [between the event and the entity appraisals] are reciprocal", thus giving an interesting avenue for the research of paradigm interactions.

According to Cropanzano et al. (2011, pp. 154), the first research to put both paradigms, the event and the entity, vis-à-vis at the same time was done by Ambrose, Hess and Ganesan (2007), who assessed the "system-related attitudes" (i.e. the social entity) of passengers as a result of a complaint handling experience (i.e. event) at the airport. The main result was that the event attitudes mediated the fairness event experience to the system-related attitudes, thus giving a hint of an existing connection between the paradigms. A follow up article (Ambrose & Schminke, 2009) strengthened these findings, setting an overall entity fairness judgement to be a full mediator between the specific event fairness judgements and the outcome variables, e.g. task performance and commitment.

The mediation role of entity fairness between the event fairness and the outcome variables (e.g. affective commitment and job satisfaction) is replicated by Jones and Martens (2009). However, for instance Choi (2008) adopted a different approach and successfully assessed the interaction between the event and the entity fairness appraisals on the outcome variables (e.g. organizational commitment or trust in managers), thus setting an interaction pattern between the two fairness paradigms.

As we can see in this chapter, these paradigms with the empiric evidence fit well in FHT. The theory makes an implicit distinction though it's not clearly articulated - the general fairness heuristic applies to the social entity in question, when, on the other hand, the information to generate the heuristic in the judgemental phase comes via events. The way those concepts are usually measured goes also hand in hand with FHT - the event fairness being measured with three or four facets (discussed in the next chapter), while the entity fairness is measured as a single trait-like dimension (Ambrose & Schminke, 2009; Choi, 2008; Cropanzano et al. 2011, pp. 154; Jones & Martens, 2009).

1.3.3. Justice facets and overall fairness

As mentioned before, there are two different approaches to fairness: a construct consisting of three – four justice facets e.g. Colquitt (2001) and a global unidimensional construct, so called overall justice (fairness) (Ambrose, Wo & Griffith, 2015).

The facet approach divides justice and subsequently fairness into distributive, procedural and interactional facets, though Colquitt (2001) divides the last mentioned further into two separate facets: interpersonal and informational facets. The fairness experience in the facet approach can be seen to form as a cognitive justice appraisal, and in comparison of what is with an individual's comparative standard. This is expressed more formally in a normative way by justice rules (Cropanzano, Fortin & Kirk, 2015).

The distributive facet, as the name says, concerns the distribution of the results, i.e. a perception of the outcomes or allocations. When an individual assesses distributive justice, one is concerned whether the received outcome is equal with another comparable individual, and whether perceived input/output ratio in an ongoing exchange is comparable with the counterpart. When these do not meet, unfairness is experienced (e.g. Adams, 1965).

The procedural facet, on the other hand, is an appraisal of information about the elements of process which led to the outcomes perceived. Areas of procedural justice are best described by the rules created by Leventhal (1980; via Cropanzano, et al. 2015). They consist of: consistency – an expectation that the procedure is applied consistently over occasions; accuracy - the process of resource allocation should be based on the best possible information and an informed opinion with a minimized possibility of error; correctability – whether there happened errors in the process, there should be an opportunity to reverse or modify the decisions; representativeness - whether concerns and interests (i.e. voice) of individuals are present and allowed during the procedures; ethicality - whether the procedures reflect ethical and moral values of the individual; and bias-suppression - an expectation of the procedure's neutrality and a lack of bias impact.

The interactional facet was originally considered as a part of the procedural facet, reflecting a social part of the procedure (Cropanzano, et al. 2015). Conceptually there are at least two parts: the level of courtesy and respect received during the procedure (i.e. interpersonal), and whether the individual had an access to all the information used during the procedure (i.e. informational). However, since thesis research is done in an area lacking social interaction per se, more detailed evaluation of this facet is not relevant.

Unidimensional overall justice research started to emerge over a decade ago, yet any systematic research on the topic can be found only within the last five years (Ambrose, et al. 2015). The author would note that the term "overall justice" might be misleading, since the surveys created to assess overall justice (e.g. Ambrose & Schminke, 2009) are measuring for the evaluative assessment of the fairness experience and not for the comparative justice standards per se. However, when the traditional facet based surveys (e.g. Colquitt, 2001) are interpreted in the sense of unidimensional latent variable, the use of the term overall justice is justified. Anyway, the concept's place in the justice/fairness construct pantheon is disputed and theoretical relations are mosaic. The overall justice (fairness) is researched as an antecedent of the other outcomes; as a consequence of the other variables (though this area has been accused of lacking the controls of the fairness facets); as a mediator of the fairness facet effects; and as a moderator of the fairness facets' effects (Ambrose, et al. 2015). However, its distinction from the facet approach is not disputed (Ambrose, et al. 2015). In this thesis a unidimensional approach is employed in the entity fairness assessment, acting as an appraised heuristic in FHT.

1.3.4. Fairness in context of pricing

Price fairness as a concept received a proper introduction via Kahneman, Knetsch, and Thaler (1986) research, questioning the status quo of the fully rational standard economic model. By this research Kahneman and colleagues proposed the dual entitlement principle, showing that not all price increases are seen negatively by the consumers, and a certain level of entitlement for the shop's surplus is seen as fair by the consumers. This principle might be seen as a derivative of distributional justice.

Since then, there have been several inquiries into the price fairness area, which have received some attention. Campbell (1999) researched the effects of inferred profit and motives on unfairness and unfairness effect on shopping intentions. However, the operationalization of fairness was done by a single question, with roots in an attributional theory and with only a weaker theory from the justice area. For instance Bolton, Warlop, and Alba (2003) researched different factors' effect on the price fairness, e.g. historical data or different price attributions, by directly asking participants for a fair price in different scenarios. Vaidyanathan and Aggarwal (2003) went a bit further with an operationalization of the price fairness via adjectives fair, acceptable and reasonable in their research of locus of causality and controllability attributions of the price fairness.

The seminal work of Xia, Monroe and Cox (2004) proposed integrated price fairness framework with an adaptation of some broader fairness theories and gave a rise to more systematic research inquiries later on. Xia et al. (2004) described fairness as just, reasonable and acceptable, and proposed that fairness and unfairness might be separate concepts. Besides the aspect of the price fairness as a cognitive comparison of a price/procedure to a relevant standard/reference, they proposed also a clear indication of what emotions could be elicited in which situation. The framework is rooted in the equity and the distributive justice theories, thus clearly being more of a distributive fairness flavor, despite the fact it does give a possibility for the comparison of the procedures.

There are only a few examples in the research of the procedural pricing fairness (or remotely resembling concepts). Xia, Kukar-Kinney and Monroe (2010) assessed the fairness of the promotion tactics, showing that it has an effect on the perceived price fairness, as well as the customer's nonmonetary effort to participate in the promotion. More clearly procedural fairness is assessed in Kukar-Kinney, Xia and Monroe (2007) where the authors assessed pricing policy fairness and its effect on the perceived price fairness and the further effect on shopping intentions. Still, further integration of the more traditional fairness traditions into the pricing context may be found in Ferguson, Ellen and Bearden (2014). The authors manipulated the procedural and the distributive justice information and examined their effect on overall price fairness achieving positive results. However, when a concept of 'a suspicion of the seller' was introduced into the model in the second study, it fully mediated the effect of the manipulated procedural justice information on overall fairness (Ferguson, et al. 2014).

Loyalty is shown to be a significant moderator between the price fairness experience and the causes of the unfairness experience (Dai, 2010). The author identified a temporal proximity of a price change and the magnitude of a price difference as being the main causes of the fairness experience. Dai (2010) also concluded that price fairness has a strong influence on the purchase satisfaction.

Schweitzer and Gibson (2008) manipulated the explanation provided during the price increase and found that the explanations which violated the community standards of fairness led to the higher experience of unfairness. To identify social norms (i.e. the community standards), Maxwell and Garbarino (2010) surveyed Americans, to find out which kind of price discrimination is more, and which is less acceptable. The main result was that the price discrimination between customers is unfair, regardless whether it is based on the purchase frequency or loyalty. Maxwell and Garbarino (2010) also concluded that though it is not a norm, surprisingly high share of the respondents were convinced that the same item should be of the same price across the retailers. This separation of price fairness into the social (i.e. the social norms of society) and the personal (i.e. the subjective evaluation of a price magnitude) aspects is successfully investigated further in Maxwell and Comer (2010) with vignettes containing different explanations for the price change.

Schweitzer and Gibson (2008) showed in their second study, even though it was not purely about pricing fairness but a mix of pricing/organizational context (i.e. receiving a wage raise vignette), that the unfairness experience leads to unethical behavior (i.e. lying about working hours), yet this behavior had positive psychological effects (including lowered anger level, higher satisfaction).

The price fairness research is predominantly based on the cognitive appraisals. Thus a particularly important inquiry was done by Faullant, Matzler and Mooradian (2013). The authors tried to assess personality (extraversion/neuroticism), price fairness and several emotions at the same time in a bank-themed vignette experiment. As expected, personality had a significant effect on the experienced emotions, and the fairness experience had a strong effect on the emotions as well. The outcome variable, in this case pricing satisfaction, was affected primarily solely by the fairness experiences, and only weakly and inconsistently by the emotions elicited by the fairness experience. The variance explained in the emotion variables is inconsistent as well.

An interesting feature of the pricing fairness research field is that there is no research in the paradigm of the entity fairness per se in conjunction with an event-style price fairness, at least none that the author is aware of. The closest to the concept of entity fairness might be found in the research by Matute-Vallejo, Bravo and Pina (2011), which assessed an effect of corporate social responsibility on price fairness and loyalty. Another good example is the research by Grewal et al. (2004) where trust was assessed as a property of an entity.

1.3.5. Fairness in context of dynamic pricing

There are only a few inquiries in the field of dynamic pricing fairness after Cox's (2001) managerial suggestions. Grewal et al. (2004) manipulated a dynamic pricing tactic between a personal identification and the time based price discrimination. The results showed that the time based price discrimination is less severe for trust, fairness and repurchase intentions, especially when there is no explanation for the discrepancy in prices (Grewal, et al. 2004). Haws and Bearden (2006) concluded in their own series of studies that especially the differences between the customers lead to the experience of unfairness (compared to a difference in time, or between the sellers). Haws and Bearden (2006) also showed that in an action-based price forming the customers tend to have higher fairness and satisfaction levels; this may be interpreted as a provision of 'voice' from procedural justice and being in line with theoretical considerations in the justice literature.

Lee et al. (2011) manipulated an illusion control (i.e. "an expectancy of a personal success probability [being] inappropriately higher than the objective probability would warrant") and a lateral consumer relationship (i.e. the reference information about other consumers' purchase details) in the context of action/group-buying, showing both of them to have an effect on the fairness experience. Hinz, Hann, and Spann (2011) conducted a study in a name-your-own-price market, manipulating the available information on the price threshold policy and the threshold policy itself (fixed (traditional) vs. adaptive (dynamic)). Hinz et al. (2011) found that providing the information about policy per se did not have an effect on the satisfaction or percentage of the accepted offers, but it had a rather significant interaction effect (adaptive policy and disclosure of that) on the both outcome variables.

All the existing evidence shows clearly that the odds are strongly against the individual level price discrimination, especially when personified, and that it leads to the unfairness experience. The fairness experience has a strong influence on the satisfaction with the purchase, and it also affects the behavioral intentions such as loyalty. There is also evidence that the unfairness experience produces emotional reactions and an unethical act of "revenge" might have a positive psychological effect for the customer. Dynamic pricing schemes, which grant the possibility of influence by the customers (i.e. 'voice'), are perceived as more fair. Being open and disclosing information about the pricing policy might have advantages for perceived fairness.

1.4. Fairness and affects

An affect is a general term to cover moods and emotions. A mood is more of a lengthier and valence based (feeling good or bad), general affective state of a lower intensity; whereas an emotion is a more specific state which lasts a shorter period of time and is tied to a specific event or target.

One might intuitively say that the fairness experience and affect are connected. Still the empiric research lags a bit. In a large review on the connection of affect and fairness Cropanzano et al. (2011) concluded that though historically fairness-related emotions were predominantly seen to be results of the fairness appraisals, recent research shows that this is not always the case - that an affect might as well be an antecedent of the fairness experience.

There are several theoretical proposals on the fairness-to-affect link, but fewer on the affect-as-cause direction, not to mention the scarcity on the integrative approach for both directions within one theoretical framework (Cropanzano, et al. 2011). Overall Cropanzano et al. (2011) concludes that the integration of the diverse field of theories coming from the justice and affect research is slow and demanding. However, Cropanzano et al. (2011) brings out integrative model proposed by Mullen (2007) as an "insightful conceptual paper".

To describe the interplay between fairness and affects, Mullen (2007) proposes her own Affective Model of Justice Reasoning (AMJR), where she divides affects into two groups based on their relation to a focal event eliciting the fairness experience: incidental affects, i.e. not related to the event per se; and integral emotions, i.e. emotions elicited by the fairness-relevant event. While reviewing the traditional fairness-to-affect direction, the model proposes also possible interpretations for the affect-to-fairness direction. This division of the incidental/integral affects follows closely with a more general description of the emotion-rationality interaction reviewed by Pham (2007).

1.4.1. Integral emotions

According to Colquitt et al. (2013) emotions as the consequences of fairness have been proposed by theories for a long time (e.g. equity theory by Adams 1965), but the empirical research came into the game much later. The authors especially mention that one study seemed to trigger a larger endeavour to integrate emotions and fairness, namely Weiss, Suckow and Cropanzano (1999). Weiss et al. (1999) successfully showed that different discrete emotions are elicited by a combination of procedural fairness treatment and positive/negative outcome result.

Cropanzano et al. (2011) consolidates the findings in his review of the empirical research and states that when disadvantaged unfairness (i.e. a perceived loss) is experienced, the experience of anger or disgust is more likely; when advantaged unfairness is experienced (i.e. a perceived gain or an own unethical behaviour), the emotions of guilt or shame are more likely to occur. This kind of an emotion-as-result way of thinking is also integrated within Xia et al. (2004) framework of the price fairness. These propositions follow a general moral-integral emotion pattern presented by Pham (2007).

Mullen (2007) and Pham (2007) both propose that the integral emotion has feedback on the original event evaluation, thus affecting the final appraisal via different routes, such as searching for a more emotion congruent information and therefore strengthening the original evaluation. It is clear that the integral emotions are seen as a central mediator between the fairness experience and behaviour (e.g. Barclay, Skarlicki, and Pugh 2005; Barclay and Kiefer 2012; Pham 2007).

However, it is worth to mention that integral affects are assessed also in the entity paradigm research, but in this case they are valence based mood evaluations because of the different time frame used in the research (Colquitt, et al. 2013; Barsky & Kaplan, 2007). Colquitt et al. (2013) especially states that there are challenges in a watertight integration of the affect and the justice research, since the different paradigms employ the different timeframes and thus the effects on affects are different.

1.4.2. Incidental affects

In her review Mullen (2007) proposes different effects of emotions and moods as the antecedents of fairness. According to Mullen (2007) mood can act directly in an affect-as-information -way or indirectly as a priming. Affect-as-information means that people would consult their mood in a situation that lacks fairness related information or when there is no need for a systematic review of the fairness related information and a gut feeling is sufficient. Instead, priming means the mood's influence on which cognitions are called into mind during the appraisal of fairness. An example of this effect may be found in the study by van den Bos (2003) where the induced valence based affectivity was shown to have a clear effect on the appraisal of fairness, when there was a lack of the relevant information. This gives support for using the mood as an affect-as-information.

However, the valence based approach is not sufficient when considering the effects of incidental emotions. Pham (2007) argues that different incidental emotions have divergent effects. Anger and sadness are both negatively valenced emotions, but they have a clear difference regarding the content and interpretation of the emotion related information. To address this difference Mullen (2007) proposed the use of Appraisal Tendency Framework (ATF) (Lerner & Keltner, 2000; Han, Lerner & Keltner, 2007), which has been used widely in research (for review: Lerner, Li, Valdesolo & Kassam, 2015). ATF postulates that each emotion has 'themes' or appraisal tendencies which are core to that specific emotion. Those tendencies consequently affect cognitive processing. For instance anger is high on a certainty appraisal dimension and thus might lead towards a higher risk-taking behaviour. Sadness, on the other hand, is low on a certainty appraisal dimension and might lead towards a more systematic assessment of the accessible information from environment. Thus ATF gives a framework for the discrete emotion effects' evaluation on fairness experience. Based on the previous research, it seems that at least anger, disgust, sadness, fear, guilt and shame are connected closely to the fairness experience (Mikula & Scherer, 1998; via Mullen, 2007). In any case, the more detailed overview of ATF is outside of this thesis' core focus - the relative impact of discrete affective states on the fairness appraisal is more interesting at this stage.

Though Mullen's (2007) integrative AMJR is a necessary step further in the consolidation of the affect and fairness related research, it is challenging that the model is mainly oriented towards the event fairness paradigm. Yet, there is some evidence for the affect being an antecedent of entity fairness. In a qualitative inquiry Hollensbe, Khazanchi, and Masterson (2008) concluded that while subjects did use the traditional information and rules for the fairness assessment about their new supervisors and companies, there were also other non-traditional sources of information present, such as the respondent's own affective state and social information. Ambrose et al. (2007) also measured the negative affectivity in the research of entity related attitudes. When the authors took affectivity into the analysis as a control variable, the fit of the model worsened a bit, though this did not alter their main conclusions. This empiric evidence gives a support that there is a connection between the affects and the entity fairness appraisals, even though the current models don't include it per se. In addition, review by Pham (2007) also suggested that a discrete emotion affects heuristics used in decision making, thus giving a pleasing possibility for linking FHT's heuristic (i.e. entity fairness) directly to the incidental emotions.

1.5. Motivation and research question

There are several motives behind this thesis. First of all, field experiments on perceived fairness in the dynamic pricing/rebating context are scarce. Second, the theme of rebating fairness, not to mention it's dynamicity, has, as far as the author knows, also not been studied earlier. Third, the concept of entity fairness has not been introduced properly in the pricing/rebate field. Fourth, the stability of entity fairness perceptions over possible phase-shifting events has not been measured in the existing research so far. Considering these motivations; an integrative approach to the interplay of event and entity fairness in the rebating context, incidental and integral emotions and the availability of information in a natural setting is needed.

As seen in the review by Cox (2001), the trials with dynamic algorithms may be risky for the company and its image. However, inspired by results of Hinz et al. (2011) (i.e., disclosing the information of pricing dynamic policy) it was hypothesized that the manipulation of the available information of the dynamic trial and algorithm functioning details should affect fairness perceptions and consequently behavioral intentions towards the company.

Based on FHT, some possibilities can be seen about interplay between event and entity fairness. The revelation of the usage of the dynamic algorithm, as seen via prism of the FHT, might be seen as a phase-shifting event. The question is whether it is so and to which extent. If the disclosure of the algorithm trial is indeed a phase-shifting event, event fairness should have an effect on the second measurement of the heuristic (entity fairness).

Yet, considering that the relationship is ongoing and the existing heuristic is fully formed, the entity fairness appraisal (i.e. heuristic) might have a limited effect on the evaluation of the event fairness appraisals as well. The heuristic is considered to be rather stable and is not easily nor quickly changeable, thus the entity fairness might have a strong stability despite the effects of event fairness. Thus:

- Research question (RQ) 1: Test different mediation models to see how the change of the heuristic (entity fairness) is mediated by event fairness appraisal

The manipulation itself, the disclosure of the trial information, should have an aversive effect on the event fairness, as known from the previous research. However, providing extra information might have a positive effect due to the lack of clear reference points. Either as the procedural information affecting procedural fairness, or as a sign of the company's openness and goodwill, having a non-specific effect on the fairness appraisal. Regardless, it is clear that the manipulation effects should affect only the event fairness and not the entity fairness - but this should be tested as well. An interesting question arises; is there any interactions between the exposure to the algorithm and the information available?

- RQ2: Assess the manipulation effect pattern and the possible interaction effects on the fairness areas.

It is unclear whether the fairness-relevant incidental affects would have an effect on the pre-manipulation entity fairness (as in Hollensbe, et al. 2008; and Pham, 2007). Or would incidental affects have a direct effect on event fairness as proposed by Mullen (2007), and could those be used as information when there is a lack of it otherwise. Thus:

- RQ3: Which path is more significant from fairness-relevant incidental affects: to event fairness or to pre-manipulation entity fairness?

Based on the previous affect-as-result research on fairness, it is clear that the integral emotions should be elicited by event fairness. Yet, as triangle tango between event fairness, entity fairness and affects is not straight-forward, as seen in RQ3:

- RQ4: Are integral emotions antecedents to entity fairness, or do they have a separate direct path from entity fairness as a consequence?
- RQ5: How strong is fairness mediation between incidental and integral affects, and do they have a direct, unmediated path?

FHT proposes that heuristic would affect behavioral intentions. On the other hand, previous research has proposed that affects mediate this effect. Thus:

- RQ6: Test which antecedent of behavioral intentions is stronger, entity fairness or integral emotions.

Final question is whether fairness is such a central concept that it would fully mediate the effects of the manipulations on the behavioral intentions? Thus:

- RQ7: Test if manipulation effects are fully mediated by fairness, or are there any direct effects on outcome variables.

For full visualized picture, with integration of all paths to be assessed, please consult Figure 1.

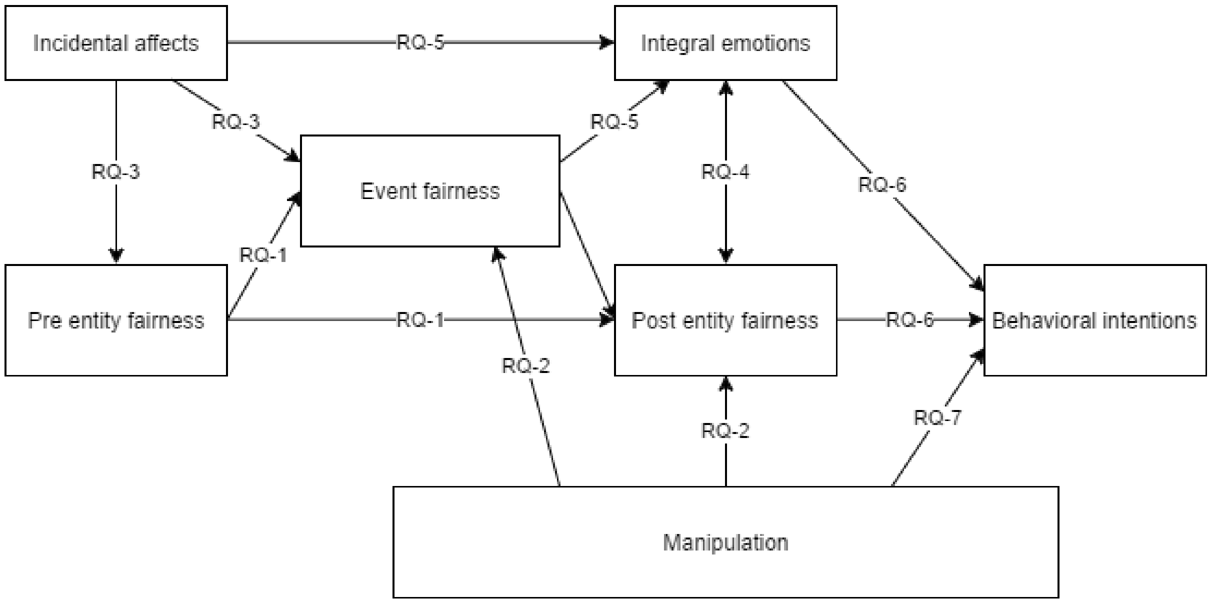


Figure 1. Visualization of paths assessed in different research questions.

2. Methodology

2.1. Research process

This study was conducted as a part of Aalto University's and University of Tampere's "Koukku - Sales Psychology to Games, Game Psychology to Selling" research project. The study was conducted with a European online rebate service provider and it was conducted at the same time as the company was running a trial that tested a dynamic pricing algorithm for adjusting its own rebating rates (c.f., Kaptein & Parvinen, 2015). The company's service works as a listing of online stores with separate set rebate rates for the each store. When a customer goes through the company's site to a certain online store and purchases goods or services, customer receives a rebate to his own account afterwards. A part of the stores presented in the service had their rebate rates adjusted by the algorithm in real time. The adjusted rebate rates were shown in the online store listing and store's individual page within company's service. It was however not controlled, which one each user saw. In the trial it was randomized whether one was shown a rebate rates based on the algorithm or whether one belonged to a control group that used the company's previous rebate rating policy (fixed pre-determined rebate rates). The group that was subjected to the algorithm was larger than the control group. The primary focus of the trial was to collect evidence from the use of the profit maximizing algorithm, which is not a part of this thesis. Data used for this thesis was gathered via a survey afterwards, while the main trial was still running.

Before conducting the main trial, six randomly chosen company's customers were interviewed. The main motivation behind the interview was to explore the customers' views about dynamic pricing and dynamic rebating. However, to avoid too clear framing of interview's theme, general information about purchase behavior on- and offline was asked, as well as some background information. Majority of the respondents raised questions about fairness of the procedure of applying dynamic pricing, including discriminative treatment of customers, social justice, and concern of the use of private information for price formation, as well as its effect on the company's image. When asked about how one would react if he/she would encounter dynamic pricing, responses were two-fold – if people believe that they make a gain, then dynamic pricing/rebating feels acceptable but less so if one would believe he/she makes a loss. Gaining or losing was attributed to the rebate rates one was given compared to other customers. Based on the interviews, fairness and emotions were chosen as topics for the research, combined with behavioral intentions as the main outcome variables.

The sample for the gathering of survey data was provided by the company. The sample contained email addresses, already randomized into manipulation groups with only one criteria: samples for treatment and control group should be of equal size. Since the treatment group that was subjected to the algorithm was larger than the control group, the clients with less recent use of the service (up to six months since the last use) were invited as well to gather an equivalent number of responses for the survey regarding the control group.

The survey was conducted in July 2016 via an email invitation sent by the researcher. Email contained a link to the survey. The email stated that the company participates in the scientific research in collaboration with Aalto University concerning customer experiences with online services. A reminder was sent a week after the original email.

The survey was designed to add a second level of manipulation: amount of provided information about the trial and the algorithm, thus producing a 2 (algorithm, control group) x 3 (no information, information level 1, information level 2) between-subject research design. In the information manipulation, the first group received neither any information about the trial nor questions about gain/loss, that is, they were the control group for information condition.

The second group (information level 1) received information about the trial with the following text: "*There is a trial in the system of the [company], where rebate rates shown to a share of clients are partly set by a person and partly set by an algorithm, which adjusts rebate rates between different display times*", followed by questions whether they think they were exposed to an algorithm or not, and whether they had gained or lost by this. After responding to these questions, the respondent was provided the information about the group he/she belonged, and continued answering to post-manipulation parts of the survey.

The third group (information level 2) followed the same steps as the second group, but with additional text providing extra information about the principles of how the algorithm works: "*The algorithm works in such a way that in the beginning it shows randomly generated rebating rates within boundaries set in advance. Later, based on feedback of the clients received through clicking, the algorithm searches optimal level for rebate rates. This means that clients who visited the site at different times might see different rebate rates. The algorithm uses group level information, but does not use clients' identified purchase history for setting rebate rates*". (See manipulation text in Finnish in Appendix A).

The data on incidental affects, personality, general satisfaction, entity fairness and the use of the company's services was gathered before the manipulation. After the manipulation, data on event fairness, entity fairness, integral emotions, behavioral intentions and background variables was gathered.

2.2. Data analysis

Because there is no clear separate integrative theory to incorporate all the parts of the research, a more data-driven approach was used when assessing the paths between the main variables of interest. Each group of variables was added one at a time, with several possible theoretically meaningful causal paths - the model with the best fit was taken to the next stage. The employed order of inclusion of the variables was: fairness' different areas, incidental affects, integral emotions, behavioral intentions.

All data was used for the measures' parallel analysis (PA), the exploratory factor analysis (EFA), the confirmatory factor analysis (CFA) and the extraction of the factor coefficients. Due to a selection bias, the sample was reduced via propensity score matching (PSM) (Randolph, Falbe, Manuel & Balloun, 2014). PSM is a statistical technique to subsample observed data based on the relevant confounding variables. The goal of PSM is to lower the effect of selection biases between the control and experiment groups. This reduced sample was used to assess the research questions.

Assessing the latent structure of the measures was done in three steps. First, the assessment of the purely theoretical structure was done using CFA. If the resulted fit indices were unacceptable, EFA was utilized to assess the loading structure. After that, CFA was rerun to confirm the modified model and to extract the estimated factor coefficients. Due to the ordinality of the data, a diagonally weighted least squares (DWLS) estimator was used, which has been shown to produce accurate parameter estimates (DiStefano & Morgan, 2014). However, DWLS-estimated standard errors are to be treated with caution (Yang-Wallentin, Jöreskog, & Luo, 2010; DiStefano & Morgan, 2014).

All EFA analysis were done with an accordance to suggestions by Baglin (2014). Since all the survey data for all the measures was ordinal, and some of the distributions were skewed, polychoric correlations were utilized. Since a data-driven approach was employed, all EFA rotations were oblique to allow possible correlation of the latent variables. An estimation of the amount of extractable factors in EFA was done with a recommendable parallel analysis (PA) (Fabrigar, Wegener, MacCallum & Strahan, 1999) when applicable. If the content interpretation of extracted loadings were meaningless, the measure's background theory was reconsulted.

When the same measure was taken twice, the time invariance test was conducted with an accordance to guide provided by Widaman, Ferrer, and Conger (2010). The test was performed by encompassing the construct's measurement models into the same structural equation model (SEM) from the both measurement times, and imposing increasingly constraining restrictions in a step-wise manner to assess the level of invariance. For the ordinally measured data the time invariance levels are: the configural invariance (i.e. the same pattern of the fixed and free factor loadings across time); the weak factorial invariance (i.e. the invariant factor loadings across time); and the strong factorial invariance (i.e. the invariant factor loadings and the intercepts across time) (Widaman, et al. 2010). A strong factorial invariance level is needed to compare differences over time (i.e. latent variable mean change). To achieve this, all the step-wisely generated SEM-models must fit the data measured by the traditional fit indices. Also, a deterioration in the fit indices, from the less restricted model to the more restricted level, is evaluated. If the decrease in fit indices is significant, and $\Delta\chi^2$ -test is significant on Δdf level, it is concluded that the lower level of invariance is achieved. However, the usual $\Delta\chi^2$ is not applicable for the ordinal data, thus the test-derivative proposed by Satorra and Bentler (2010) is being used.

Several fit indices are reported for CFA and SEM. The reported indices are: χ2 -test, Comparative Fit Index (CFI), root mean squared error of approximation (RMSEA), standardized root mean squared residual (SRMR), and for CFA weighted root mean square residual (WRMR) is also reported. It is common knowledge that χ^2 -test is too sensitive for a larger sample size and thus should not be used as a reason to abandon the model, if the rest of the fit indices are acceptable. For the general thumb cutoff rules, Hu and Bentler (1999) proposed .95 for CFI (higher - better), .08 for SRMR (lower - better) and .06 for RMSEA (lower - better). For WRMR Yu (2002) proposed a cutoff at 1.0 (the lower, the better).

Unfortunately, CFI, SRMR, RMSEA and WRMR are all calculated based on the model's degrees of freedom, thus it is impossible to calculate them for the just identified (df = 0) models. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are reported when comparisons with such models are made. Since AIC and BIC are only comparative fit indices, there are now cut-off rules, but the scheme of the lower, the better is used when the competing models are being compared.

Two measures are reported for the reliability of the assessment: Cronbach's α for the theoretically constructed scales (to honor traditions), and a member of omega-family - the composite reliability (Raykov, 2001) for the CFA-extracted values. Both act in a manner in which scores closer to 1.0 are better and 0.7 being a reasonable cutoff for a good reliability. Average variance extracted (AVE) is reported for the measurements' convergent validity, with the interpretation being the higher, the better.

To assess the research questions SEM was performed for the PSM-ed data with extracted factor coefficients in the CFA-stage of the analysis. ML estimator was used at this stage.

All statistical analysis was performed in RStudio -software (RStudio Team, 2016) run on R v.3.3.2 (R Core Team, 2016) with the following libraries: lavaan v.0.5-22 (Rosseel, 2012) for CFA, SEM and time invariance assessment, psych v.1.6.12 (Revelle, 2016) for the

Chronbach's α, PA, EFA and polychoric correlations; semTools v.0.4-14 (Pornprasertmanit, Miller, Schoemann, Rosseel, Quick, et al. 2013) for CR and AVE; MatchIt v.2.4-21 (Ho, Imai, King & Stuart, 2011) for PSM.

2.3. Subjects

In a total 6950 invitation emails were sent to the company's randomly selected clients divided nearly equally between the algorithm exposure groups, receiving n=559 full valid responses; n=357 (10.3% response rate) for the algorithm group and n=202 (5.8% response rate) for the non-algorithm group. The division between the manipulation groups is presented in Table 1.

The algorithm and the non-algorithm groups did not differ on gender, education or the household size. The algorithm group was statistically significantly younger (M=34.99, SD=11.06) than the non-algorithm group (M=39.25, SD=14.08); t(342.45)=3.70, p<.001. Detailed information on demographic variables is presented in Table 2.

The groups didn't differ on bonuscard use, however the algorithm group participants were a bit more frequent online shoppers. The groups did have a significant difference on the variables concerning the relationship with the company, the algorithm group participants having a longer customership, slightly more frequent use of the company's services and being generally bit more satisfied with the company. The shopping background variables and the customer relationship variables are presented in Table 3 and 4 respectively.

Table 1. Frequencies and relative share of sample within different manipulation groups, separately for original algorithm and non-algorithm groups, and for PSM-matched algorithm group.

	Algorithm		Non algorithm		PSM-match	
Variable	n	%	n	%	n	%
Information condition						
Control group	76	*21.3*	50	*24.8*	42	*20.8*
Information, level 1	133	*37.3*	73	*36.1*	73	*36.1*
Information, level 2	148	*41.5*	79	*39.1*	87	*43.1*

Because of the difference of the groups, PSM (Randolph et al. 2014) was performed based on the variables showing statistically significant difference between the groups (age, online shopping and customer relationship variables), thus reducing the final size of the algorithm group to n=202. Though the only difference on the frequency of online shopping could be diminished fully between the groups, the level of difference's statistical significance on other variables could be reduced substantially. E.g. age for the PSM-matched algorithm groups was 36.32 (SD=11.90); thus the statistical difference to the non-algorithm group was smaller but still statistically significant: $t(391.18)=2.26$, $p=.024$. The detailed information on the influence of PSM on the background variables can be seen in Table 1, 2, 3, and 4.

Table 2. Subjects' demographic background variables, frequencies and relative share, separately for the original algorithm and the non-algorithm groups, and for the PSM-matched algorithm group.

	Algorithm		Non algorithm		PSM-match	
Variable	n	%	n	%	n	%
Gender						
Male	90	*25.2*	62	*30.7*	49	*24.3*
Female	267	*74.8*	140	*69.3*	153	*75.7*
Education						
Basic school or corresponding	31	*8.7*	15	*7.4*	20	*10.0*
Vocational school	83	*23.2*	48	*23.8*	52	*25.7*
Senior high school	61	*17.1*	38	*18.8*	33	*16.3*
Polytechnic degree	88	*24.6*	58	*28.7*	49	*24.3*
University degree	85	*23.8*	40	*19.8*	42	*20.8*
Postgraduate degree (licentiate/phd)	9	*2.5*	3	*1.4*	6	*3.0*
Size of household						
1	104	*29.1*	52	*25.7*	53	*26.2*
2	139	*38.9*	80	*39.6*	86	*42.6*
3	48	*13.4*	30	*14.9*	30	*14.9*
4	40	*11.2*	24	*11.9*	21	*10.4*
5	18	*5.0*	11	*5.4*	7	*3.5*
>5	7	*2.0*	2	*1.0*	5	*2.5*

NOTE: Age information is presented in the text.

Table 3. Subjects' shopping related background variables, frequencies and relative share, separately for the original algorithm and the non-algorithm groups, and for the PSM-matched algorithm group

	Algorithm		Non algorithm		PSM-match	
Variable	n	%	n	%	n	%
How often do you use bonuscards?						
Never, or does not own	5	*1.4*	11	*5.4*	5	*2.5*
Once a year or less	4	*1.1*	0	*0.0*	4	*2.0*
Few times a year	15	*4.2*	7	*3.5*	10	*5.0*
At least once a month	23	*6.4*	11	*5.4*	13	*6.4*
At least once a week	122	*34.2*	67	*33.2*	68	*33.7*
Daily, or almost daily	188	*52.7*	106	*52.5*	102	*50.5*
How often do you buy services or goods online?	*** [a]					
Never shopped online	0	*0.0*	1	*0.5*	0	*0.0*
Once a year or less	3	*0.8*	6	*3.0*	3	*1.5*
Few times a year	109	*30.5*	106	*52.5*	95	*47.0*
At least once a month	213	*59.7*	74	*36.6*	92	*45.5*
At least once a week	28	*7.8*	15	*7.4*	10	*5.0*
Daily, or almost daily	4	*1.1*	0	*0.0*	2	*1.0*

NOTE: [a] the significance level of χ^2 -test of frequency table difference of the observation distribution between the non-algorithm and either of the algorithm groups.
*** p<.001. ** p<.01. * p<.05.

Table 4. Subjects' company relationship background variables, frequencies and relative share, separately for the original algorithm and the non-algorithm groups, and for the PSM-matched algorithm group

	Algorithm		Non algorithm		PSM-match	
Variable	n	%	n	%	n	%
For how long have you been using services of the company?	*** [a]					*** [a]
Less than a week	3	*0.8*	18	*8.9*	3	*1.5*
Less than a month	24	*6.7*	11	*5.4*	18	*8.9*
Less than half a year	27	*7.6*	30	*14.9*	21	*10.4*
Less than a year	38	*10.6*	34	*16.8*	23	*11.4*
A year or longer	265	*74.2*	109	*54.0*	137	*67.8*

Continued next page

Continued from previous page:						
How often do you use services of the company?	*** [a]				** [a]	
Once a year or less	20	*5.6*	46	*22.8*	19	*9.4*
Few times a year	196	*54.9*	123	*60.9*	144	*71.3*
At least once a month	132	*37.0*	31	*15.3*	36	*17.8*
At least once a week	9	*2.5*	2	*1.0*	3	*1.5*
At least once a day	0	*0.0*	0	*0.0*	0	*0.0*
I am generally satisfied with the services by the company	*** [a]				** [a]	
Completely disagree	9	*2.5*	7	*3.5*	6	*3.0*
Somewhat disagree	13	*3.6*	7	*3.5*	10	*5.0*
Not agree, nor disagree	20	*5.6*	45	*22.3*	18	*8.9*
Somewhat agree	157	*44.0*	91	*45.0*	94	*46.5*
Completely agree	158	*44.3*	52	*25.7*	74	*36.6*

NOTE: [a] the significance level of χ^2 -test of frequency table difference of the observation distribution between the non-algorithm and either of the algorithm groups.
*** p<.001. ** p<.01. * p<.05.

2.4. Measures

2.4.1. Fairness

There were no available measures for the online rebating fairness experience in the pricing context (at least in the knowledge of the researcher), thus a review of the different fairness measures was conducted from the contexts of organizational event fairness (Colquitt, 2001; Elovainio, et al. 2010) and pricing fairness (Campbell, 1999; Vaidyanathan & Aggarwal 2003; Grewal, et al. 2004; Herrmann, et al. 2007; Xia, et al. 2010). As a result new measures were composed for event fairness with procedural and distributive subscales (see full Finnish version in Appendix B).

The event fairness measure consisted of two subscales, distributive and procedural. The distributive scale consisted of four items, “*Rebate percentage I saw is fair*”, “*Rebate percentage I saw is reasonable*”, “*Rebate percentage I saw is acceptable*” and “*Rebate percentage I saw is balanced with my effort*”. The procedural scale consisted of three items “*Way of determining rebate percentage is understandable*”, “*Way of determining rebate percentage is regular*” and “*Way of determining rebate percentage treats all clients in the same matter*”. The reliability (Chronbach’s α) for unmodified scales was .89 for the distributional scale and .85 for the procedural scale. However, the purely theory-based measurement model in CFA produced unacceptable fit indices: $\chi^2[13, N = 559] = 167.75$, $p < .001$, CFI = .984, RMSEA = .146, SRMR = .033, WRMR = 1.098. EFA was performed to assess the loading structure of the items. PA suggested, as expected, two factors, thus leading to extracting two factors in EFA with oblique rotation. Item "Rebate percentage I saw is reasonable" showed significant crossloading for the both scales. Because the Finnish version of the question could indeed be semantically interpreted to belong to either scales, the crossloading was allowed. During CFA rerun also one residual error correlation was allowed based on the modification indices. The adjusted model of the event fairness measure produced more acceptable fit indices in CFA: $\chi^2[11, N = 559] = 45.3$, $p < .001$, CFI = .996, RMSEA = .075, SRMR = .018, WRMR = .561, with model's total CR of .93 and AVE of .76. The adjusted measurement model with the standardized loadings is presented in Figure 2, and EFA loading matrix is presented in Appendix C. The correlation between the latent variables of distributive scale and procedural scale was .74 thus being just enough to make a conclusion of them being separate constructs, though closely connected.

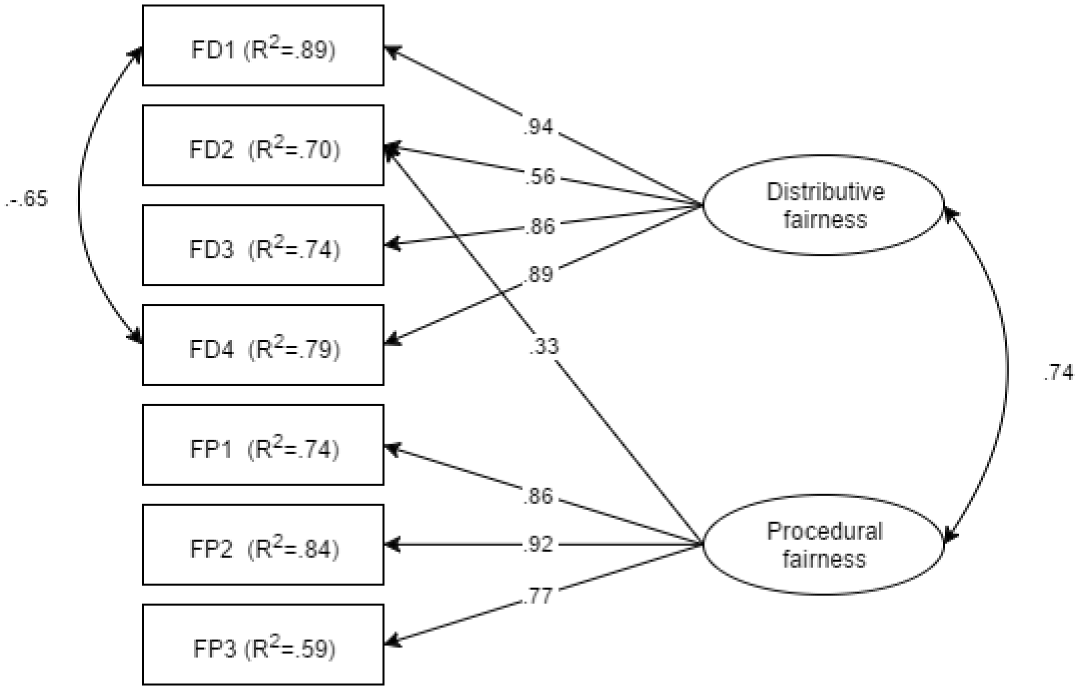


Figure 2. The measurement model for the event fairness measure, the standardized solution (N=559). Straight arrow depict loadings, curved double-head arrows depict latent variable or measurement error covariance. All parameters are significant at p<.001.

For entity fairness, the scales from Ambrose and Schminke (2009) and Choi (2008) were consulted, and as a result creating adapted entity fairness measure of three items: "*[Company] usually treats me fairly*", "*[Company] is fair company*" and "*Just is suitable word to describe the [company]*". The entity fairness measurement was done prior (pre) to the manipulation and repeated after the manipulation (post). The reliability (Chronbach's α / CR) for the both measurement times was .93 / .92, whereas AVE was .86 for the pre-measurement and .87 for the post-measurement. CFA indices could not be calculated separately due to the measurement model being just-identified, i.e. the degrees of freedom equals 0. Because the construct was measured twice, there was a possibility to assess the construct invariance over time. The time invariance analysis was performed according to the guidelines by Widaman et al. (2010), achieving a strong time invariance of the construct. The formed model of the strong time invariance is presented in Appendix D. The fit indices of the model are: $\chi^2[3, N = 559] = 6.93$, $p = .074$, CFI = 1.000, RMSEA = .048, SRMR = .007, WRMR = .323.

2.4.2. Incidental affects and integral emotions

When choosing a suitable measurement tool, the decision was altered by considerations like, whether the same tool could be used for two different time frames with different instructions, i.e. incidental affects – emotions felt during last day and integral emotions - feeling right now; and whether it covers more affects/emotions, and not purely the valence based positive/negative -continuum as used quite often in economics' research. Boyle, Helmes, Matthews, and Izard (2015) provided a good overview of the available tools. Two measures were chosen for the final consideration: Positive and Negative Affect Schedule - Expanded Form, PANAS-X (Watson & Clark, 1999) and Differential Emotions Scale, DES-IV (Izard, Libero, Putnam & Haynes, 1993). DES-IV was chosen due to the fact of facets being of more basic emotions aspects and items consisting more of sentences and behavior descriptions than purely rely one-word-adjectives' items. The scale was translated into Finnish for this thesis.

DES-IV consist of 12 scales, one to each discrete basic affect (interest, enjoyment, surprise, sadness, anger, disgust, contempt, guilt, shame, shyness, hostility inwards), each having three items, e.g. "*Feel like you feel when something unexpected happens*", "*Feel sheepish, like you do not want to be seen*" or "*Feel so interested in what you're doing, caught up in it*". The measurement was taken twice: before the manipulation with instruction "*How much did you feel like this during the last day*", i.e. incidental affects; and after manipulation with instruction "*How much do you feel like this right now*", i.e. integral emotions. The reliability (Chronbach's α) of the scales varied between .68 and .90, see details in Table 5.

The theory based CFA fit produced a non-positive definite matrix of covariance and a latent correlation over 1 between the shame and shyness -scales. After a close inspection, two items from those scales had semantically too close meaning, i.e. "Feel embarrassed when anybody sees you make a mistake" and "Feel bashful, embarrassed". The residual covariation of those two items was allowed and the results of modified CFA are in Table 5. Latents' correlation matrix varied between -.40 and .95 for the incidental affects, and -.37 and .94 for the integral emotions, thus indicating severe clustering of some scales, questioning the measure's quality.

Table 5. DES-IV reliability, fit and invariance details

	Incidental affects, i.e. pre-manipulation	Integral emotions, i.e. post-manipulation	Achieved time invariance level
Reliability (Chronbach's α)			
Interest	.77	.83	Strong
Enjoyment	.81	.84	Non invariant
Surprise	.80	.84	Strong
Sadness	.86	.87	Strong
Anger	.84	.87	Strong
Disgust	.70	.87	Configural
Contempt	.70	.68	Strong
Fear	.82	.88	Strong
Guilt	.82	.86	Configural
Shame	.76	.84	Configural
Shyness	.77	.81	Strong
Hostility inwards	.84	.90	Configural
Fit indicies			
χ^2[527, N = 559]	1234.18	1301.33	
p	<.001	<.001	
CFI	.967	.975	
RMSEA	.049	.051	
SRMR	.059	.071	
WRMR	1.166	1.211	
Total CR	.96	.98	
Total AVE	.69	.80	

Because the measure was taken twice, the time invariance test was performed. Sample size was insufficient to run the time invariance test on the whole DES-IV at once, thus each scale was tested separately. See reliability, fit indices and achieved time invariance level in the Table 5. The detailed information on scales' time invariance test is provided in Appendix E.

It is noteworthy, that although the theoretical construction was kept, PA and EFA were performed to see more detailed loading structure. PA suggested seven to eight factors for the both measuring times, suggesting that there might be some redundancy in the construct. EFA loading structure also showed a certain level of clustering which differs across the measurement times, thus giving a reason to doubt whether the same theoretical construct is measured under different instruction provided. However, a more detailed review of this is out of the scope of this thesis.

Inclusion of DES-IV scales in the final analysis was dependent on two conditions - whether the time-invariance test provided a strong invariance level giving confidence that the same construct is measured over two measurement times; and fairness relevance. Thus the scales included in the final analysis were: interest, surprise, sadness, anger, contempt, and fear.

2.4.3. Behavioral intentions

Zeithaml, Berry and Parasuraman (1996) proposed Behavioral-Intentions Battery (BIB) to measure, and e.g. Parasuraman, Zeithaml and Malhotra (2005) included Loyalty intentions -scale as a part of E-RecS-QUAL scale. However, BIB is designed to capture a typical sale interaction pattern of a customer relationship, whereas rebate service in question does not charge money from the consumers. Other matters to be considered in the research context are the lack of alternatives or other noteworthy competitors at the moment of the research. Thus, the adapted and translated version of BIB has been used, including all the items of the loyalty scale, i.e. "*I'm going to say positive things about [the company]*", "*I'm going to recommend [the company] to someone who seeks your advice*", "*I'm going to encourage friends and relatives to do business with [the company]*" and "*[The company] is my first choice in rebating services*", both items of switch scale, i.e. "*I'm going to do more business with [the company] in the next few years*" and "*I'm going to do less business with [the company] in the next few years*", two items from external response scale, i.e. "*I'm going* *to complain to other customers if I experience a problem with [the company]'s service*” and “*I’m going to complain to external agencies, such as the [local alternative* of Better Business *Bureau], if I experience a problem with [the company]'s service*” as well as only item from internal response “*I’m going to complain to [the company]'s customer service, if i experience a problem with [the company]'s service*”.

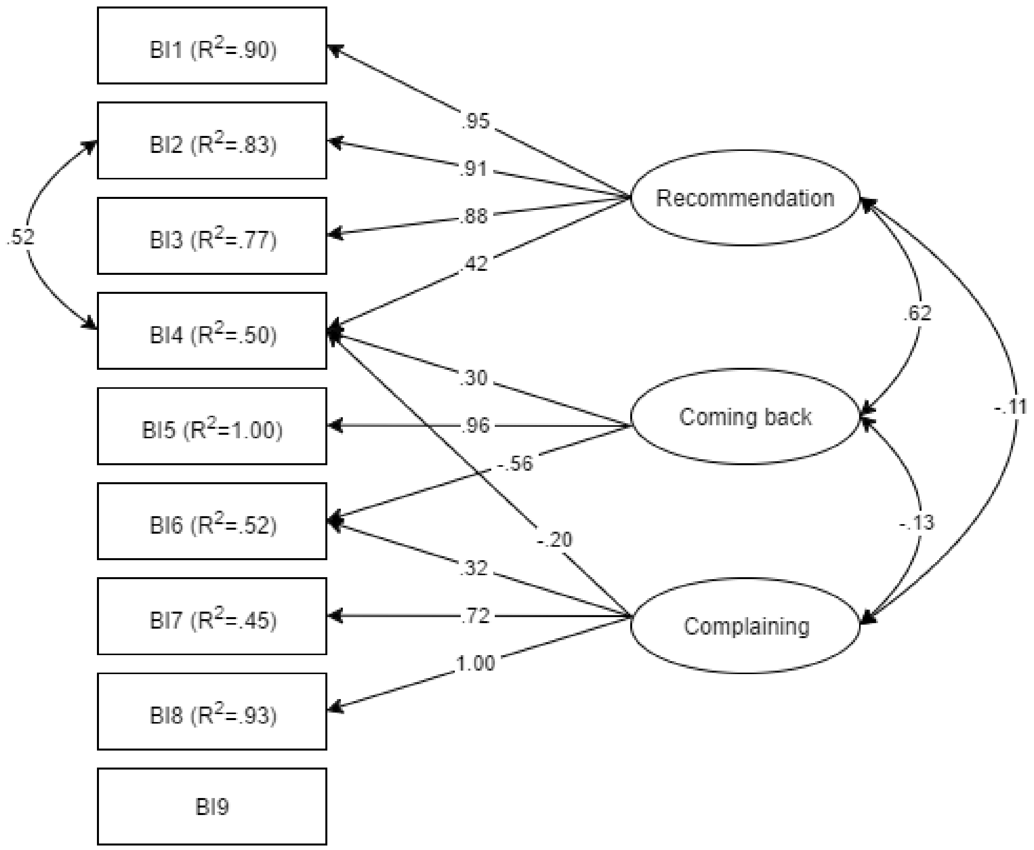


Figure 3. The measurement model for the behavioral intentions’ measure, the standardized solution (N=559). Straight arrow depict loadings, curved double-head arrows depict latent variable or measurement error covariance. All loadings, the measurement error and the recommendation-coming back covariances are significant at p<.001. The complaining-coming back covariance is significant at level p<.01. The recommendation-complaining covariance is significant at p<.05.

The theory-based measurement model CFA calculation could not produce robust fit indices due to the latent covariance matrix not being positive definite. EFA was performed to assess the loading structure of the items, extracting PA’s suggested four factors in an obliquely rotated solution. However, after inspecting the solution, the loading structure wasn’t clear, and the internal response scale’s only item showed significantly low communality of .23 compared to the average of the other items’ communalities .77 thus leading to exclusion of the item from the further analysis. The rerun of PA with a reduced amount of items still suggested four factors, even though the EFA-extracted loading matrix showed the fourth factor to be more of an odd-come-shorts of variance without any meaningful interpretation, thereby leading to sticking to the three factor solution extraction. Based on the EFA extracted solution and CFA's modification indices feedback, the adjusted measurement model was obtained, with two items crossloading and one residual error correlation, producing acceptable fit indices: $\chi^2[13, N = 559] = 46.11$, $p < .001$, CFI = .996, RMSEA = .068, SRMR = .021, WRMR = .476, with model's total CR of .83 and AVE of .74. The adjusted model with the standardized loadings is presented in Figure 3 and the EFA loading matrices are presented in Appendix D. The extracted three factors were given new names, to not to confuse them with the original's - recommendation, complaining and coming back. The latents' correlations settled between -.13 (complaining and coming back) and .62 (recommendation and coming back), thus giving an indication of the constructs being separate.

2.4.4. Other measures

The second and the third information condition group (the ones that got the disclosure of the trial) were asked in which group they believed they belonged, before they were given the algorithm/control group information disclosure. The distribution did not vary between the manipulation groups ($\chi^2[6, N = 433] = 0.53$, $p = .997$) setting on average for 64.3% being unsure, 12.9% believing in being exposed to algorithm, 23.2% believing in that they saw only rebate rates decided by a human.

These same two groups were also asked whether they think they had lost or gained in this trial. The distribution didn't vary between groups ($\chi^2[6, N = 433] = 7.59$, $p = .260$), giving on average 85.3% of unsure, 7.1% believing in their own loss in the situation, 7.7% in their own gain. The variance of this variable is too low to be included in the analysis.

Manipulation checks were done for the second and the third information condition groups. For the algorithm condition, participants were asked to which group (rates set by algorithm/human) they really belonged ($\chi^2[2, N = 433] = 215.85$, $p < .001$). For the information condition, they were asked whether they did receive information on how the algorithm worked ($\chi^2[2, N = 433] = 93.15$, $p < .001$). There was, however, a considerable proportion of those who answered "don't remember" to the manipulation checks, on average 25.6% for the algorithm check and 21.9% the information check. Despite that, the manipulations can be seen as quite successful.

Also, Big-5 personality profile was gathered with Short Five -inventory (Konstabel et al., in press). However, theory-based CFA produced such poor fit indices (χ^2[395, N = 559] = 2977.83, p < .001, CFI = .699, RMSEA = .108, SRMR = .108, WRMR = 2.513) that it was discarded from the analysis.

3. Results

3.1. Event fairness mediation of entity fairness change

To assess the event fairness mediation of the entity fairness change, three models (presented in Figure 4) were matched one against another in SEM using the extracted factor coefficients. The models are: no mediation model, i.e. event fairness, affects only the post-manipulation entity fairness with a direct path from the pre-manipulation entity fairness included; partially mediated model, i.e. event fairness mediates the effect of the pre-manipulation entity fairness on the post-manipulation entity fairness with direct path included; and fully mediated model, i.e. event fairness fully mediates the effect with a direct path excluded between the pre- and the post-manipulation entity fairness.

Since the correlation of distributive and procedural scales was high, the covariation of the variables was allowed in all models. The model's fit indices can be seen in Table 6. The fully mediated and the no mediation models are unacceptable based on the SEM fit indices. Because the partially mediated model has 0 degrees of freedom, the rest of the comparison was done based on AIC and BIC indices. The partially mediated model has the smallest values of AIC and BIC, thus supporting the model as the best fit for the data. The resulted partial mediation model's parameters are presented in Figure 5.

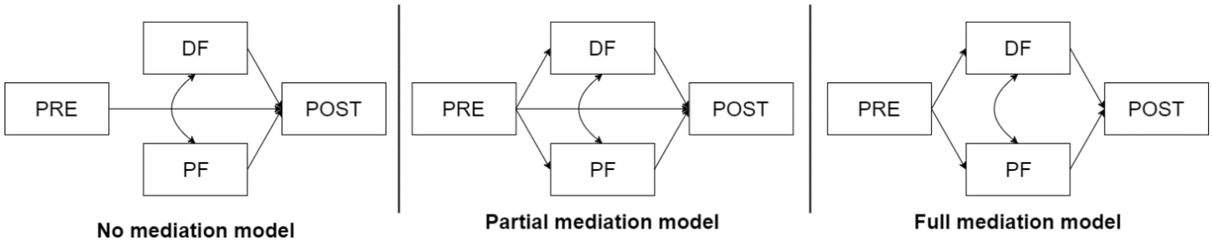


Figure 4. Tested fairness mediation models. Straight arrow depict regressions, curved double-head arrows depict covariance.

Abbreviations: PRE: pre-manipulation entity fairness; POST: post-manipulation entity fairness; DF: distributive fairness; and PF: procedural fairness.

Table 6. Event fairness mediation of entity fairness - model comparison

Models	df	χ^2[N=404]	p	CFI	RMSEA	SRMR	AIC	BIC
No mediation	2	124.99	<.001	.888	.390	.263	2907.33	2939.34
Partially mediated	0	-	-	-	-	-	2784.35	2820.36
Fully mediated	1	263.91	<.001	.761	.807	.142	3046.27	3078.28

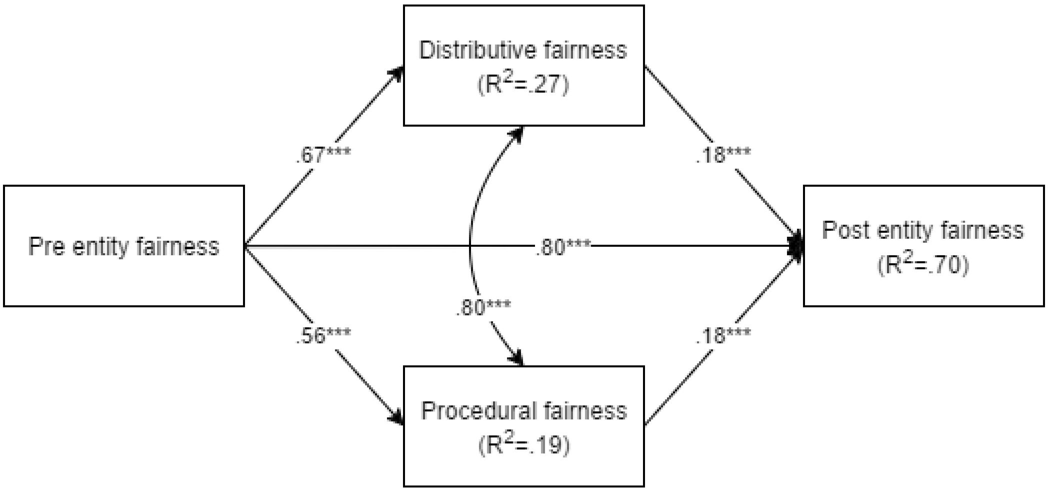


Figure 5. The partial mediation model parameters and R^2, standardized solution (N=404). Straight arrow depict regressions, curved double-head arrows depict covariance. All parameters are significant at p<.001.

3.2. The effect of the manipulations on fairness

To assess the manipulations' effect, the manipulation variables (i.e. algorithm, information level 1, information level 2) were added to the above mentioned fairness partial mediation model with the paths to the event fairness' variables. To check for the event fairness mediative effect, paths to the post-manipulation entity fairness were added as well. The second step was to add the manipulations' interaction terms to the model. The results of the both models are presented in the Table 7.

As expected, the post-manipulation entity fairness was not affected directly by the manipulations and the effects were fully mediated via event fairness. Thus, the paths from the manipulations' variables to post-manipulation fairness were excluded from the further analysis.

Table 7. The main and interaction standardized effects of the manipulation variables on event fairness

	Interaction terms excluded [a]	Interaction terms included [a]
Paths to distributive:		
algorithm	*n.s.*	.41 *
information 1	-.40 ***	*n.s.*
information 2	*n.s.*	*n.s.*
alg x info 1		-.61 **
alg x info 2		*n.s.*
Paths to procedural:		
algorithm	*n.s.*	*n.s.*
information 1	-.42 ***	*n.s.*
information 2	*n.s.*	*n.s.*
alg x info 1		-.55 *
alg x info 2		*n.s.*
Paths to post-entity:		
algorithm	*n.s.*	*n.s.*
information 1	*n.s.*	*n.s.*
information 2	*n.s.*	*n.s.*
alg x info 1		*n.s.*
alg x info 2		*n.s.*

[a] - models are just-identified, thus calculation of the comparative fit indices is impossible *** p<.001. ** p<.01. * p<.05

The event fairness results were more mixed. Information level 1 manipulation shows a significant separate effect when the interaction terms were not included. However, when the interaction terms were taken into account, the picture changes: the interaction term of the algorithm and the information level 1 showed to mediate an effect on a significant level on both event fairness areas; while the algorithm manipulation showed a separate effect only on distributive fairness. To illustrate the effect, see Figure 6.

To control the background variables, they were added as covariates on the event fairness areas and on the post-manipulation entity fairness. These included background variables were: the use period of the company's services, the activity of the company's service use, the general satisfaction for the company, gender, age, education, the household size, the frequency of online shopping and the frequency of bonuscard use. The detailed information is presented in Table 8. None of the background variables showed significant effect on the post-manipulation entity fairness. Four variables showed significant covariation with either of the event fairness areas: the use period of the company's services, the general satisfaction with the company, education and bonuscard use frequence. The adjusted model with the omitted post-manipulation entity fairness effects produced these fit indices: $\chi^2[14, N = 404] = 20.77$, p=.108. CFI=.994, RMSEA=.035, SRMR=.009. The manipulations' effects on event fairness didn't significantly change as a result of controlling for the mentioned three background variables. The background variables were kept in the model as covariates in further analyses.

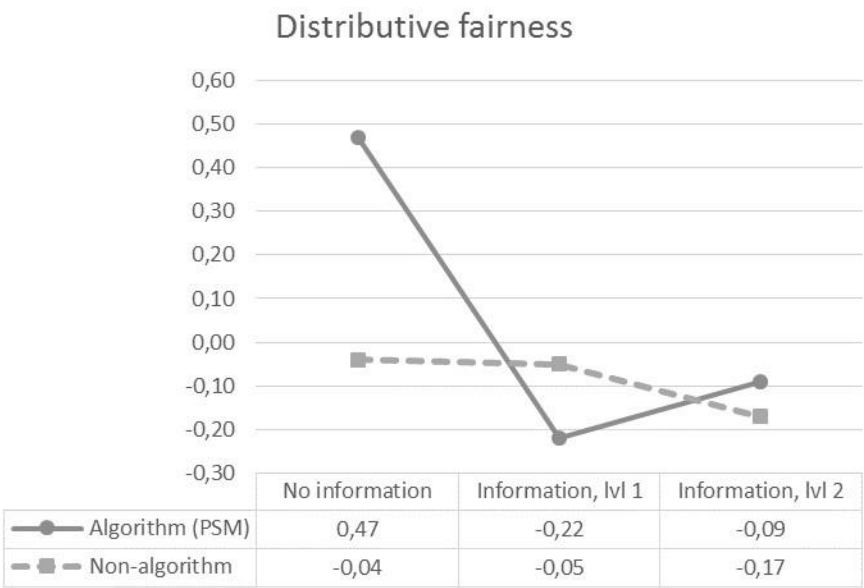


Figure 6. The difference of distributional fairness between groups.

Table 8. The path weights of covariated background variables on fairness different areas

	Distributive	Procedural	Post-entity
Background variables			
use period of the company's services	*n.s.*	-.10 *	*n.s.*
activity of company's service use	*n.s.*	*n.s.*	*n.s.*
general satisfaction for the company	.16 *	*n.s.*	*n.s.*
gender	*n.s.*	*n.s.*	*n.s.*
age	*n.s.*	*n.s.*	*n.s.*
education	*n.s.*	-.09 **	*n.s.*
household size	*n.s.*	*n.s.*	*n.s.*
frequency of online shopping	*n.s.*	*n.s.*	*n.s.*
frequency of bonuscard use	*n.s.*	.09 *	*n.s.*

Note: *** p<.001. ** p<.01. * p<.05

3.3. The role of incidental affects in fairness experiences

Two models were compared to assess the influence path of the incidental affects (interest, surprise, sadness, anger, contempt, and fear) (presented in Figure 7). The first model included paths from the incidental affects to the pre-manipulation entity fairness, whereas the second model included paths to both event fairness subareas.

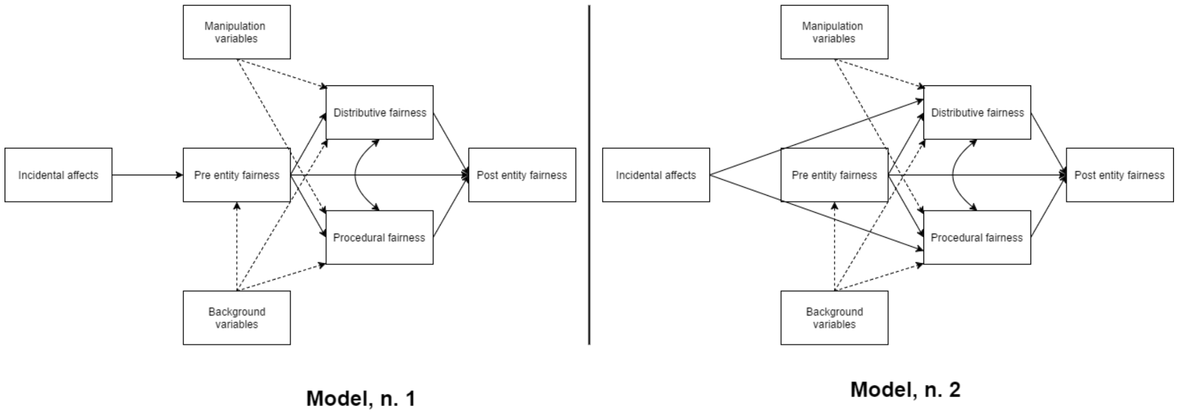


Figure 7. The tested incidental affects' effect models. Straight arrows depict regressions, curved double-head arrows depict covariance. Dotted lines represent several paths for the whole variable group.

In the first model with affect-to-entity paths fit indices were: $\chi^2[37, N = 404] = 38.51$, $p=.401$. CFI=.999, RMSEA=.010, SRMR=.012. In the second model with affect-to-event paths fit indices were: $\chi^2[31, N = 404] = 43.37$, $p=.069$. CFI=.992, RMSEA=.031, SRMR=.010. These both models are fitting well to the data, affect-to-entity being marginally better. Upon a closer inspection, affect-to-event model did not contain any statistically significant paths from the affects to the event fairness areas. Instead, the affect-to-entity model contained statistically significant paths from sadness and contempt on $p<.05$ level. Therefore the affect-to-entity model was used for the further analysis.

3.4. Integral emotions and fairness

Corresponding integral emotions' variables (interest, surprise, sadness, anger, contempt, and fear) were added to the initial model with the paths from the both event fairness facets to test the integral emotions as a consequence of event fairness. The produced model had a really poor fit: $\chi^2[109, N = 404] = 1057.89$, $p<.001$. CFI=.824, RMSEA=.147, SRMR=.136. The inspection of the modification indices revealed significant vis-a-vis paths between the incidental affects and the integral emotions. When these paths were added in, the model fit improved significantly and became just barely acceptable: $\chi^2[103, N = 404] = 283.36$, p<.001. CFI=.967, RMSEA=.066, SRMR=.066. When controlled for confounding background variables, there were no significant paths from the event fairness areas to the integral emotions.

Several models were tested to address different possible patterns in the event fairness, the post manipulation entity fairness and the integral emotions. In the first model the integral emotions were set as the mediator between the event fairness and the entity fairness. The model fit was unacceptable: $\chi^2[118, N = 404] = 2339.35$, p<.001. CFI=.588, RMSEA=.216, SRMR=.068, rendering it unusable. The second model assessed the path vice versa, the entity fairness being an antecedent of the integral emotions and therefore producing a better fit: $\chi^2[103, N = 404] = 282.10$, p<.001. CFI=.967, RMSEA=.066, SRMR=.065. This second model also contained several significant paths of interest.

The last step was to assess, whether the theory-based path between the event fairness and the integral emotions is needed for this dataset. The model, after the removal of mentioned paths, produced quite the same fit: $\chi^2[115, N = 404] = 290.54$, p<.001. CFI=.967, RMSEA=.061, SRMR=.065. This model was kept as a simpler one for the further analysis. The model is presented in Figure 8.

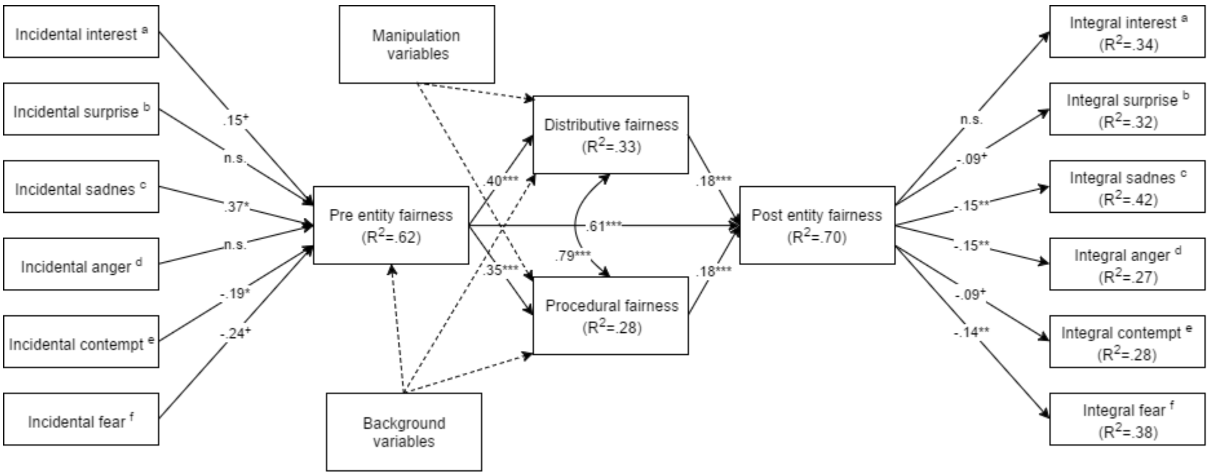


Figure 8. The final model incorporating fairness, incidental affects and integral emotions with the main parameter standardized estimates and R^2. Omitted paths: background variables regressed on all integral emotions; [a] .79***; [b] .86***; [c] .81***; [d] .69***; [e] .67***; [f] .80***. Dotted lines represent several paths for the whole variable group.

*** p<.001. ** p<.01. * p<.05. $^+$ p<.10

3.5. The effects of fairness and integral emotions on behavioral intentions

The next step was to test which antecedent of the behavioral intentions was stronger, the entity fairness or the integral emotions. To do so two models were produced for comparison once again. The first model assumed that the integral emotions mediate fully the effect of fairness on the behavioral intentions. This model fit was unacceptable: $\chi^2[175, N = 404] = 2517.93$, $p<.001$. CFI=.610, RMSEA=.182, SRMR=.069. The second model assumed that the emotions did not mediate effect on the behavioral intentions, but the post manipulation entity fairness had a direct effect. This model produced acceptable fit: $\chi^2[157, N = 404] = 355.35$, $p<.001$. CFI=.967, RMSEA=.056, SRMR=.060. The resulted model is presented in Figure 9.

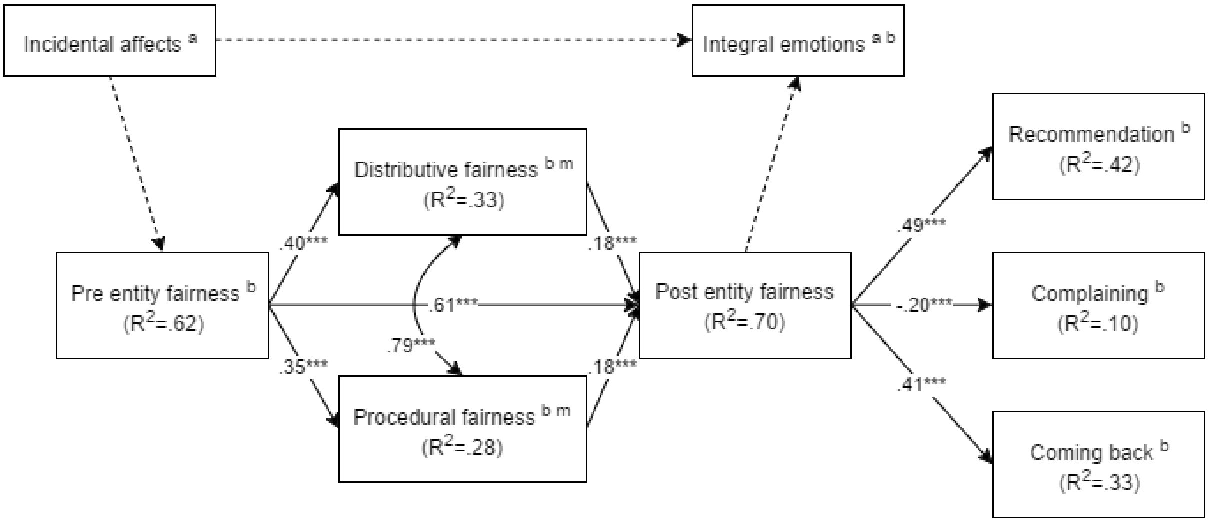


Figure 9. The model incorporating fairness, incidental affects, integral emotions and behavioral intentions with the main parameter standardized estimates and R^2. Dotted lines represent several paths for the whole variable group. The background variables ([b]) are controlled in event fairness, the integral emotions and the behavioral intentions. The manipulation variables are covariated on the event fairness ([m]).

[a] Vis-à-vis paths from the incidental affect to the integral emotions.

*** p<.001. ** p<.01. * p<.05.

3.5. The final model

As a last step, the manipulation variables were added as confounding variables of the behavioral intentions to see whether all effects are mediated by fairness. The resulted model had a good fit: $\chi^2[142, N = 404] = 324.71$, $p<.001$, CFI=.970, RMSEA=.056, SRMR=.060. This resulted model (presented in Figure 10) showed that fairness did not mediate all the effects of manipulations. The details of the background covariates and the manipulation variable effects on the behavioral intention variables are presented in Table 9.

Table 9. The effect of manipulations' and the background variables on the behavioral intentions

	Recommendation	Complaining	Coming back
Manipulations			
algorithm	*n.s.*	*n.s.*	*n.s.*
information 1	-.32 *	*n.s.*	*n.s.*
information 2	.34 **	*n.s.*	.33 **
alg x info 1	*n.s.*	*n.s.*	*n.s.*
alg x info 2	-.53 **	*n.s.*	*n.s.*
Background variables			
use period of the company's services	*n.s.*	-.17 ***	*n.s.*
activity of company's service use	.29 ***	*n.s.*	.18 *
general satisfaction for the company	*n.s.*	*n.s.*	.15 **
gender	-.22 *	*n.s.*	*n.s.*
age	*n.s.*	-.01 *	*n.s.*
education	*n.s.*	*n.s.*	-.07 *
household size	*n.s.*	*n.s.*	*n.s.*
frequency of online shopping	*n.s.*	*n.s.*	*n.s.*
frequency of bonuscard use	*n.s.*	*n.s.*	*n.s.*

*** p<.001. ** p<.01. * p<.05.

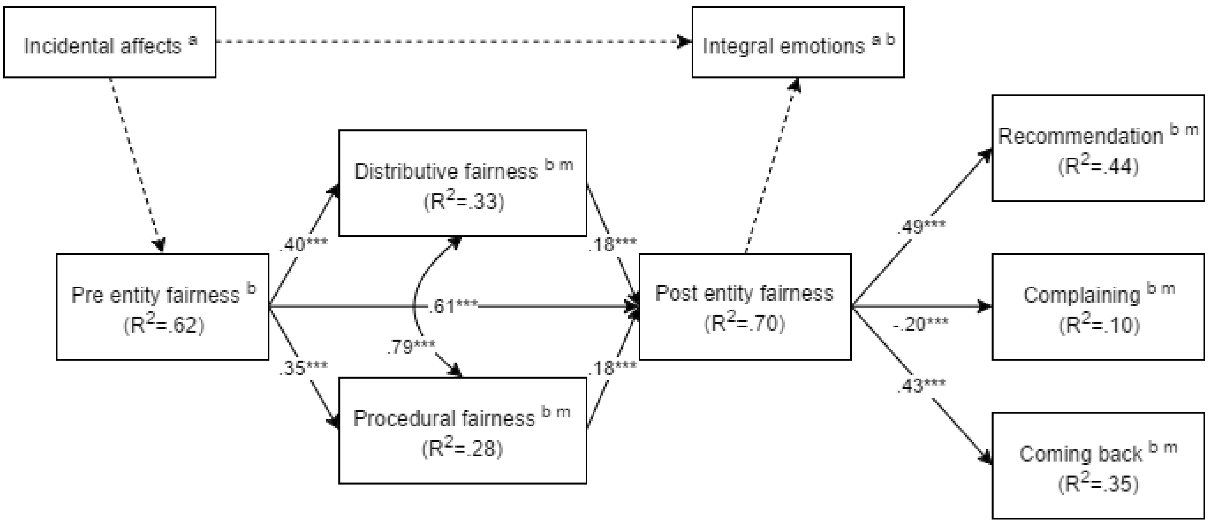


Figure 10. The final model incorporating fairness, the incidental affects, the integral emotions, the behavioral intentions and the non-mediated manipulation effects on the behavioral intentions with the main parameter standardized estimates and R^2. Dotted lines represent several paths for the whole variable group. The background variables ([b]) are controlled. The manipulation variables are covariated on ([m]). ([a]) Vis-à-vis paths from the incidental affect to the integral emotions.

*** p<.001. ** p<.01. * p<.05. $^+$ p<.10

4. Discussion

4.1. The interplay of manipulations, entity and event fairness

This is so far, as known by the author, the first research to clearly introduce the entity fairness concept into a pricing fairness context. Its meditative effect between event fairness and behavioral outcomes is replicated and in line with earlier organizational research (Ambrose & Schminke, 2009; Jones & Martens, 2009). What differs in this research, is an accounting for a theoretically proposed bidirectional interaction between entity and event fairness (Cropanzano, et al. 2001). Also, as seen in the context of overall fairness research, its interactions with the fairness' facets and outcomes are mosaic and the research is done with the different pairings of antecedent-consequence (Ambrose, et al. 2015). This research examined both of the possible routes at once - the overall entity fairness perception as an antecedent and as a consequence of event fairness, thus providing several fresh insights. First, both of the routes proved to be significant thus supporting the proposed bidirectional interaction – they are discussed later. Secondly, the separate direct path between the measurement times of overall entity fairness was evident and strong.

Despite the fact that overall entity fairness showed to be rather stable between the pre- and post-manipulation measurement times, as seen in the form of direct path's weight in SEM, due to only a small time difference between measures (minutes), one could dispute whether the concept is stable or not in the end. Therefore further investigation is needed. To assess this, the differential level of stability between the manipulation groups is illustrated in Figure 11. As seen, the non-algorithm group shows basically no change within the construct between the information groups, when, on the other hand, the algorithm group shows some changes between the different information groups. Though none of the manipulation variables is significantly affecting post-manipulation entity fairness per se, speculation might be fruitful. Especially as there might be something, besides the event fairness, that moderates the change.

The illustrated effect might be simply due to the selection bias, the algorithm exposure group having more pro-company customers on average (details in chapter 2.2.). Another possibility is the fact that within the manipulation both groups' participants were explicitly told whether they were exposed to algorithm or not, thus giving a reason for a stronger reaction within the algorithm group for being treated differently.

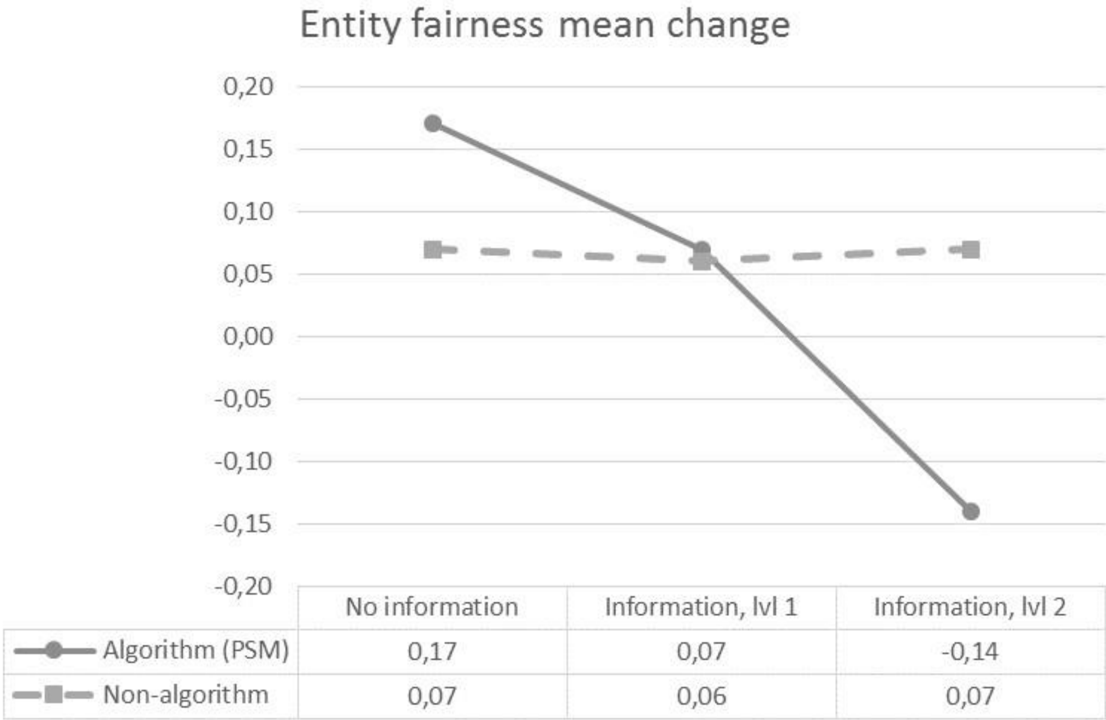


Figure 11. The mean change between the pre-manipulation and the post-manipulation entity fairness.

For the selection bias, one plausible explanation is that the algorithm group participants had a tighter psychological contract with the entity of the company, thus the use of the dynamic algorithm was seen as a breach in this contract. This kind of a breach has adverse effects on outcomes (e.g. Eckerd, Hill, Boyer, Donohue & Ward, 2013). For the examination of this change, an application of a different background theory, namely social exchange theory, might be applicable as done in a large meta-analysis by Colquitt et al. (2013). Colquitt and colleagues showed that the social exchange theory's key elements, such as trust and commitment, were in a central mediative role between fairness perceptions and outcomes. An innovative approach and use of this theory's elements as mediators or moderators of entity fairness change might be fruitful. Besides that, an interesting avenue for further research is definitely longitudinal assessment of entity fairness within longer timeframes, to see its stability and change over weeks or months, especially in a relation to justice-relevant events.

For the second possible explanation of the illustrated effect, the manipulation per se, it might be due to the fact that the algorithm exposure group received a kind of a referent point via this explicit information of being in the exposure group. As known from the previous research (e.g. Grewal, et al. 2004; Haws & Bearden 2006), the differences between the customers lead towards the unfairness experience with a higher probability, compared to other reasons. It is up to further investigation, whether this kind of explicit exposure to a group belonging information is a critical matter.

Coming to event fairness, which showed to be clearly a separate construct from entity fairness. This would be in line with the paradigm differences proposed earlier (e.g. Cropanzano, et al. 2011). Both of the measured facets of event fairness were evident, though highly correlated (.74). The correlation is significantly higher than one would expect based on the previous organizational research (.34 in Colquitt, et al. 2001), but closer to what is seen in the pricing research (.69 in Kukar-Kinney, et al. 2007). This raises a relevant question, whether the both facets should be measured in the pricing context, when the shared variance is of so high degree. Especially considering Ferguson et al. (2014) results, where the procedural justice manipulation did not have a direct effect on perceived overall price fairness, when the concept of "suspicion of the seller" was included into the model. The procedural justice information is relevant, as shown in the aforementioned studies, but as this study and Ferguson et al. (2014) results suggest, an overall approach to perceived price fairness or entity fairness might be more fruitful in the pricing context.

It is an interesting observation that the explained variance of event fairness is moderate, even though pre-manipulation entity fairness, the manipulations and the background variables are regressed on the facets. Especially in a contrast with a significantly higher level of explained variance in the entity fairness variables. What could be behind the unexplained variance within these two variables is an area of fruitful field of debate, but the possibilities are myriad and thus way too broad to be discussed here. The key observation still being that even entity fairness, in the role of FHT heuristic, does not explain but a part of event fairness variance.

Besides the explained variance and the correlation of the event fairness facets, a difference in path weights coming to the facets and leaving from them to entity fairness, is important to notice. Paths coming from pre-manipulation entity fairness to the event fairness' facets show to have about double the weight compared to the leaving paths. This can be interpreted with the help of FHT's proposed primacy effect. Older fairness-relevant information has a higher degree of effect on the heuristic, and the heuristic, in turn, has a stronger effect on newer encounters, thus explaining the stronger effect of pre-manipulation entity fairness on event fairness than the other way around. This is in line with the research examples provided by Lind (2001).

As already said, the manipulation did not have any significant effects on entity fairness, thus being fully mediated by event fairness. The manipulations' effects on event fairness, on the other hand, were incoherent and non-consistent with the expectations. With the interaction terms excluded, only the first level of the information manipulation (no details on the algorithm's logic provided) showed the expected negative effect on the both event fairness facets. This effect was expected as it has been hypothesized that the algorithm exposure would be an anticipated violation of distributive justice. When the interaction terms were included, the information manipulation lost its main effect altogether, but the interaction with the algorithm manipulation appeared to have a significant effect. This showed that the first level of the information manipulation had a divergent effect on the algorithm and non-algorithm groups, as illustrated in Figure 6. The second level of the information manipulation (the detailed text on the algorithm's logic) had no main nor interaction effects on fairness, thus ruling out its expected protective influence on the fairness experience. Its protective effect was hypothesized to be a result of the provision of procedural justice relevant information, or as an honest act of goodwill. The inconsistent finding is that after the inclusion of the interaction terms, the algorithm manipulation showed an effect only on distributive fairness, and the effect was positive.

The observed pattern of the manipulations' effects can be interpreted in the same manner as done with the entity fairness change. One explanation being the selection bias, which might especially be seen in the difference of the algorithm and non-algorithm groups in the no information condition (Figure 6). On the other hand, the manipulation itself, giving the explicit group belonging information, could have given a kind of a referent point, thus leading to the lower level of perceived experience.

It is somehow discouraging to notice that the extra information did not have any effect. It provides further evidence that the encountered real dynamic pricing is primarily seen in a negative way despite the framing or the extra information. Regardless of this, there is also one encouraging finding. Though fairness was not affected by the provision of the extra information, it did have a direct non-mediated effect on the positive behavioral intentions (coming back and recommending). This raises a question if the detailed information provision and the framing neutralizes the effect to some extent when it comes to intentions, even though dynamicity is perceived unfair per se. So, was the second level information manipulation seen as procedurally relevant or as related to goodwill in this setting? Since it didn't affect fairness perceptions, it shouldn't be regarded as justice relevant information. Thus the interpretation of this manipulation is inclined towards goodwill relatedness.

4.2. The role of affects

To answer the research question no. 3, incidental affects showed higher relatedness to entity fairness than to event fairness, which is in line with the qualitative findings of Hollensbe, et al. (2008) and theoretical propositions of Pham (2007), and does not support Mullen's (2007) theoretical propositions. This suggests that the fairness heuristic is closer to the affects than the cognitive justice rule -based appraisals of event fairness. However, the magnitude of the effect was low. From the assessed discrete incidental affects, only six made it to the final analysis due to measuring challenges. From these six, only sadness and contempt showed significant, and interest and fear almost significant effects. Surprise and anger did not show any effect.

The results with the integral emotions were interesting as well. Integral emotions didn't show to have the hypothesized significant effect from event fairness, as the majority of theories suggest (c.f., Cropanzano, et al. 2011). They also didn't have an effect on post-manipulation entity fairness, yet they showed to be a consequence of entity fairness itself. Post-manipulation fairness showed to have an effect on almost all integral emotions: significant on sadness, anger and fear; almost significant on surprise and contempt; and no effect on interest.

When it comes to the lack of relationship between event fairness and affects, one research should be considered. Schoefer and Diamantopoulos (2008) researched the mediation of emotions and they concluded that the different facets are mediated differently, interactional fairness being the most influential and the most mediated facet from the presented three facets of fairness. Thus the non-existent affect-event fairness link in the current research might be due to the fact that in the current research context, interpersonal fairness is not relevant per se, when, on the other hand, distributional and procedural fairness are not so heavily emotion-intensive.

The results also show clearly that the change from incidental affects to integral emotions is not fully mediated by fairness, and there is a strong direct vis-a-vis path from corresponding the incidental affect to the integral emotion. Despite the laboratory evidence that fairness and emotions are connected (for review Cropanzano, et al. 2011), and the empirical evidence of the relationship between fairness and valence-based affect (e.g.

Colquitt, et al. 2013), this study suggests that the pattern of the interaction between fairness and affects needs to be re-evaluated in a non-laboratory context. The results in this research show that affects and fairness are two separate tracks with a rather low level of common interaction - fairness mediates only a fraction of affect's change. However, this being said, there is still a connection of some level between these two. Especially sadness and anger-themed affects (anger, contempt) showed a more systematic relationship to fairness.

It is somehow confusing that incident sadness had a positive effect on pre-manipulation entity fairness and, on the other hand, integral sadness was negatively affected by post-manipulation entity fairness. There is no clear interpretation that can be given to this effect. Integral sadness as a result of entity fairness is understandable – experienced "irrevocable loss" (core appraisal tendency, Keltner & Lerner, 2010), could lead to a reaction like "Et tu, Brute". However, there is not any plausible intuitive explanation for the positive effect of incidental sadness on entity fairness.

The negative effect of incidental contempt on entity fairness is in line with its core action tendency to "lower the reputation of the perpetrator" (Keltner & Lerner, 2010). Meaning that the experienced higher incidental contempt would lead to a mental discount of the other's reputation, an evaluation of entity's fairness included. An experience of anger is traditionally connected to an experience of unfairness (e.g. equity theory by Adams, 1965) and this link is seen in this research as well. A higher post-manipulation entity fairness led to a lower integral anger, and vice versa, a lower entity fairness led to a higher experience of integral anger. Anger is usually connected to restorative actions as a result of offense against self.

Integral fear had also a significant effect from post-manipulation entity fairness. When fear's core tendency is taken into account (i.e. "an imminent threat to self", Keltner & Lerner, 2010), it might provide an interesting avenue for the interpretation – did certain people interpret the use of the algorithm as a threat to the self? This might give an interesting insight on how dynamic pricing might be viewed.

Taking together the links and especially both, fear and anger, the indication is that the concept of self, in connection to entity's appraisals, might have a significant role. Does one's evaluation of the vulnerability of the self, or self-esteem, have a role in the process of fairness appraisals? Cropanzano, et al. (2011) suggests in their own review that the self appraisal might have a bigger role, but research is limited and more inquiries are needed.

Though there are previous evidence of emotions' meditative effect between fairness and behavioral outcomes (e.g. Colquitt, et al. 2013), there were no such findings in this study. Integral emotions did not show any meditative effects between fairness and behavioral intentions and served only as separate outcome variables. There is no clear indication why. It might be due to the reason, that the context of the research might be less intensive emotionally (e.g. the lack of interpersonal interaction per se), thus leading to a separateness of the emotional reactions.

4.3. Limitations

One of this research's fortes is ecological validity. It is done outside of the laboratory and not with vignette-based approach, but with real customers and a real company, as opposed to the majority of the dynamic pricing fairness research. Also, the research adopted the non-identifying dynamic algorithm, which addresses the results of the negative reactions towards the identifying techniques in the dynamic pricing, thus giving further insight into the topic.

Despite strengths, there are several limitations in this research. First of all, the customer relationship with the participated company is based on a reverse money transactions scheme, which differs from the usual pricing contexts. Therefore, the trade-off the customers have to think of, is about the amount of money received versus the trouble of using the company's site, which is much less severe compared to the traditional buying context. This might have an effect on the results, as mentioned above, in the form of lower emotional intensity and thus fairness being appraised as less important.

Second, the data gathering itself. The data was gathered with emailed survey, after the use of the service was over. The temporal proximity of the use of the service and the survey response was not controlled, thus providing a hint that the fairness appraisal did not apply to the use of the service per se, but to the reception of the information about the algorithm trial. On one hand, this gave a possibility to gather a large amount of psychometric data and thus providing quite rich insights into the interaction of the several heavy-to-measure concepts. On the other hand, it should be considered in the future research, whether a shorter questionaries could be carried out on the spot, within the visit on the company's site, or to explicitly control for the time between the service event and the survey response.

Third, the selection bias. The exposure to the algorithm wasn't controlled due to technical reasons. The participants exposed to the algorithm were more pro-company (more active users with higher average satisfaction towards company) on average compared to the control group. This might produce certain issues with the interpretability of the results, even despite PSM was used. However, this limitation was tried to be controlled for on the course of the whole research and results' interpretations.

The fourth caution is related to measures used in this research. Though the detailed overview of the used measures' psychometrics is out of this thesis' scope, it is worth to mention that some problems might be related to how the measures behaved. The measure of behavioral intentions was adapted to this context by removing the money-related items. This way of adaptation induced severe problems with the measurement model. The move can be reconsidered in future research. There were also a couple of problems regarding DES-IV. As the EFA rotations and the time invariance tests showed, the loading structure is different between the different time instructions. Therefore discrete emotions at this very moment and discrete affects experienced for the past-X-(input your time measure) don't seem to follow precisely the same structure. This limited the assessment of the effect of discrete affects severely, since measures' invariance is unquestionable premise for the comparison. A separate mention is needed concerning the psychometrics of the used personality measure. The theory-based model's fit was unacceptably low and therefore it couldn't be used. However, there is some evidence that personality and trait affectivity might have its own role in the fairness reactions and have high interaction with the emotion reactions perceived (Skarlicki, Folger & Tesluk, 1999; Colquitt, Scott, Judge & Shaw 2006; van den Bos, Maas, Waldring & Semin 2003).

Fifth, the operationalization of incidental affects needs to be re-considered. A mixed mood-emotion approach was chosen intentionally to achieve the possibility of a discrete state assessment but it could possibly be the cause for the mixed results as well. Thus, further inquiry into the topic, with a more strict distinction between mood, emotion and e.g. trait affectivity might prove to be highly fruitful.

Sixth, a control for financial involvement. As became clear at the interview stage, the research population is really unwilling to disclose any financial background information. Due to the protection of anonymity, there were no requests given to the company concerning the possibility to receive log entries about e.g. transaction monetary value. Yet, this information could potentially provide further moderator insights into the interplay of perceived fairness and the other variables.

Seventh, the gain/loss perception control didn't work. The variance of the non-forced choice responses was so low that the variable information couldn't be used in the analysis, despite it potentially providing a really important piece of data. It could unveil some of the dynamics behind perceived fairness. This is a topic to consider in the further research.

A separate mention should be pointed to the fact that it wasn't controlled in the survey, which of the stores had the algorithm adjusted rebate levels and what kind of online stores the participants were generally using. If the adjusted rates were presented in the stores that weren't related to the user's ordinary behavioral habits, it could soften the fairness reactions. Perceptions and inclinations towards each online store in principle, might also affect the evaluation of the rebate rate fairness as well. However, this is speculation only, due to the lack of these controls.

Albeit the limitations and considerations are relevant, this research is still of high value, especially as the high ecological validity and the vast degree of concepts assessed at once give insights into the interplay between those and provide the indications of the possible further inquiries.

4.4. Future research

This research might well be one of the first ones to assess the stability of entity fairness per se, albeit for a quite short timeframe (minutes). Therefore, additional inquiries are necessary to find out under which conditions the stability of entity fairness is perceived and, on the other hand, what happens to it over different time frames. Also a more systematic research of different operationalizations of fairness (facet vs overall) for different paradigmas (event/entity) is needed, especially with consultance of Cropanzano, et al. (2015) commentaries.

Because the link between entity fairness and discrete affect states is established, further integration of entity fairness and discrete emotions in the field studies would be beneficial. To specify the results of discrete emotions, it would be beneficial to control the target of the emotions assessed, since it was not done in this research per se. Further systematic inquiry into the use of the heuristic when discrete affective states are ongoing, is also needed. As the discrete emotions have a significant effect from entity fairness, like hypothesized earlier, it might be interesting to assess the involvement of different self evaluations (vulnerability, self-esteem, etc). This might provide a fruitful area for inquiries.

As mentioned earlier, there was data gathered about Big-5 personality, but it was rendered useless as the measurement tool didn't behave as expected. But, since there is some evidence that the reactivity to unfairness differs between individuals, it would be beneficial to assess personality or the other relevant traits simultaneously with affects. Also, better tools could be used for the discrete emotion assessment. As Weidman, Steckler and Tracy

(2017) shows, there is some level of ambiguity in the emotion research field andclosing all the loopholes in the operationalizations of discrete emotions could provide more reliable results. Also, as personality has been previously shown to affect fairness perceptions, one might consider assessing the behavioral styles towards the service use. Do the cherrypickers differ from the rest? Or does bargain hunting somehow affect the interpretation of situational cues, thus fueling the different perception of fairness?

A separate mention is needed on a possible different way of assessing several background and outcome variables to raise the ecological validity even further. Several background variables of company relationship were self-reported, as well as the outcome behavioral intentions. However, in terms of the fairness reactions, it should be insightful to actually have an access to the company's log entries and have the actual data on those background variables. Also, measuring the actual activity after the information disclosure, without inquiring the intentions per se, would improve the aforementioned ecological validity.

4.5. Conclusions

Considering the question presented in the thesis' topic, does honesty pay back, the simplest answer is that partly yes. Providing the full detailed information did not affect fairness in a positive manner per se, but it did have an encouraging positive effect on the behavioral intentions' outcomes.

5. Acknowledgments

Lauri Palomäki for helping with translation of DES-IV.

References

Adams, J. Stacy. 1965. "Inequity In Social Exchange." In Advances in Experimental Social Psychology, edited by Leonard Berkowitz, 2:267–99. Academic Press.

Ambrose, Maureen, Ronald L. Hess, and Shankar Ganesan. 2007. "The Relationship between Justice and Attitudes: An Examination of Justice Effects on Event and System-Related Attitudes." Organizational Behavior and Human Decision Processes 103 (1): 21–36.

Ambrose, Maureen L., and Marshall Schminke. 2009. "The Role of Overall Justice

Judgments in Organizational Justice Research: A Test of Mediation." The Journal of Applied Psychology 94 (2). psycnet.apa.org: 491–500.

Ambrose, M. L., Dxh Wo, and M. D. Griffith. 2015. "Overall Justice: Past, Present." In The Oxford Handbook of Justice in the Workplace, edited by R. Cropanzano and M. L. Ambrose. books.google.com.

Arbore, Alessandro, and Zachary Estes. 2013. "Loyalty Program Structure and Consumers' Perceptions of Status: Feeling Special in a Grocery Store?" Journal of Retailing and Consumer Services 20 (5): 439–44.

Baglin, James. 2014. "Improving Your Exploratory Factor Analysis for Ordinal Data: A Demonstration Using FACTOR." Practical Assessment, Research & Evaluation 19 (5). University of Maryland: 2.

Barclay, Laurie J., and Tina Kiefer. 2012. "Approach or Avoid? Exploring Overall Justice and the Differential Effects of Positive and Negative Emotions." Journal of Management, April. SAGE PublicationsSage CA: Los Angeles, CA. doi:10.1177/0149206312441833.

Barclay, Laurie J., Daniel P. Skarlicki, and S. Douglas Pugh. 2005. "Exploring the Role of Emotions in Injustice Perceptions and Retaliation." The Journal of Applied Psychology 90 (4). psycnet.apa.org: 629–43.

Barsky, Adam, and Seth A. Kaplan. 2007. "If You Feel Bad, It's Unfair: A Quantitative Synthesis of Affect and Organizational Justice Perceptions." The Journal of Applied Psychology 92 (1): 286–95.

Bolton, Lisa E., Luk Warlop, and Joseph W. Alba. 2003. "Consumer Perceptions of Price (un) Fairness." The Journal of Consumer Research 29 (4). The Oxford University Press: 474–91.

Bos, Kees van den. 2003. "On the Subjective Quality of Social Justice: The Role of Affect as Information in the Psychology of Justice Judgments." Journal of Personality and Social Psychology 85 (3). psycnet.apa.org: 482–98.

Bos, Kees van den, Marjolein Maas, Ismintha E. Waldring, and Gün R. Semin. 2003. "Toward Understanding the Psychology of Reactions to Perceived Fairness: The Role of Affect Intensity." Social Justice Research 16 (2). Kluwer Academic Publishers-Plenum Publishers: 151–68.

Boyle, Gregory J., Edward Helmes, Gerald Matthews, and Carroll E. Izard. 2015. “Measures of Affect Dimensions.” In Measures of Personality and Social Psychological Constructs, 190–224. San Diego: Academic Press.

Brosnan, Sarah F. 2006. “Nonhuman Species’ Reactions to Inequity and Their Implications for Fairness.” Social Justice Research 19 (2). Springer: 153–85.

Brown, Joseph D. 1999. “A Motivational Segmentation Basis for Rebates and Influencing Affective and Behavioral Attributes.” Journal of Food Products Marketing 5 (3): 9–17.

Campbell, Margaret C. 1999. “Perceptions of Price Unfairness: Antecedents and Consequences.” JMR, Journal of Marketing Research 36 (2). American Marketing Association: 187–99.

Chebat, Jean-Charles, and Witold Slusarczyk. 2005. “How Emotions Mediate the Effects of Perceived Justice on Loyalty in Service Recovery Situations: An Empirical Study.” Journal of Business Research 58 (5). Elsevier: 664–73.

Choi, Jaepil. 2008. “Event Justice Perceptions and Employees’ Reactions: Perceptions of Social Entity Justice as a Moderator.” The Journal of Applied Psychology 93 (3): 513–28.

Coker, Kesha K., Deepa Pillai, and Siva K. Balasubramanian. 2010. “Delay-discounting Rewards from Consumer Sales Promotions.” Journal of Product & Brand Management 19 (7): 487–95.

Colquitt, J. A. 2001. “On the Dimensionality of Organizational Justice: A Construct Validation of a Measure.” The Journal of Applied Psychology 86 (3). psycnet.apa.org: 386–400.

Colquitt, J. A., D. E. Conlon, M. J. Wesson, C. O. Porter, and K. Y. Ng. 2001. “Justice at the Millennium: A Meta-Analytic Review of 25 Years of Organizational Justice Research.” The Journal of Applied Psychology 86 (3): 425–45.

Colquitt, Jason A., Brent A. Scott, Timothy A. Judge, and John C. Shaw. 2006. “Justice and Personality: Using Integrative Theories to Derive Moderators of Justice Effects.” Organizational Behavior and Human Decision Processes 100 (1): 110–27.

Colquitt, Jason A., Brent A. Scott, Jessica B. Rodell, David M. Long, Cindy P. Zapata, Donald E. Conlon, and Michael J. Wesson. 2013. “Justice at the Millennium, a

Decade Later: A Meta-Analytic Test of Social Exchange and Affect-Based Perspectives.” The Journal of Applied Psychology 98 (2): 199–236.

Cortiñas, Mónica, Margarita Elorz, and José Miguel Múgica. 2008. “The Use of Loyalty-Cards Databases: Differences in Regular Price and Discount Sensitivity in the Brand Choice Decision between Card and Non-Card Holders.” Journal of Retailing and Consumer Services 15 (1). Elsevier: 52–62.

Cox, Jennifer Lyn. 2001. “Can Differential Prices Be Fair?” Journal of Product & Brand Management 10 (5): 264–75.

Cropanzano, R., M. Fortin, and J. F. Kirk. 2015. “How Do We Know When We Are Treated Fairly? Justice Rules and Fairness Judgments.” In Research in Personnel and Human Resources Management, 33:279–350. Emerald Group Publishing Ltd.

Cropanzano, Russell, Zinta S. Byrne, D. Ramona Bobocel, and Deborah E. Rupp. 2001. “Moral Virtues, Fairness Heuristics, Social Entities, and Other Denizens of Organizational Justice.” Journal of Vocational Behavior 58 (2). Elsevier: 164–209.

Cropanzano, Russell, Jordan H. Stein, Thierry Nadisic, and Others. 2011. Social Justice and the Experience of Emotion. Routledge.

Dai, Bo. 2010. “The Impact of Perceived Price Fairness of Dynamic Pricing on Customer Satisfaction and Behavioral Intentions: The Moderating Role of Customer Loyalty.” Auburn University. http://holocron.lib.auburn.edu/handle/10415/2217.

Davis, Douglas D., and Edward L. Millner. 2005. “Rebates, Matches, and Consumer Behavior.” Southern Economic Journal 72 (2). Southern Economic Association: 410–21.

DiStefano, Christine, and Grant B. Morgan. 2014. “A Comparison of Diagonal Weighted Least Squares Robust Estimation Techniques for Ordinal Data.” Structural Equation Modeling: A Multidisciplinary Journal 21 (3): 425–38.

Dorotic, Matilda, Tammo H. A. Bijmolt, and Peter C. Verhoef. 2012. “Loyalty Programmes: Current Knowledge and Research Directions*.” International Journal of Management Reviews 14 (3). Blackwell Publishing Ltd: 217–37.

Dreze, X., and J. Nunes. 2007. “Recurring Goals: The Effect of Divisibility and Goal Attainment on Self-Efficacy and Effort.” Marshall School of Business Working Paper No. papers.ssrn.com. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=995248.

Eckerd, Stephanie, James Hill, Kenneth K. Boyer, Karen Donohue, and Peter T. Ward. 2013. “The Relative Impact of Attribute, Severity, and Timing of Psychological Contract Breach on Behavioral and Attitudinal Outcomes.” Journal of Operations Management 31 (7–8): 567–78.

Elmaghraby, Wedad, and Pınar Keskinocak. 2003. “Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices, and Future Directions.” Management Science 49 (10): 1287–1309.

Elovainio, Marko, Tarja Heponiemi, Hannamaria Kuusio, Timo Sinervo, Taina Hintsa, and Anna-Mari Aalto. 2010. “Developing a Short Measure of Organizational Justice: A Multisample Health Professionals Study.” Journal of Occupational and Environmental Medicine / American College of Occupational and Environmental Medicine 52 (11). journals.lww.com: 1068–74.

Fabrigar, Leandre R., Duane T. Wegener, Robert C. MacCallum, and Erin J. Strahan. 1999. “Evaluating the Use of Exploratory Factor Analysis in Psychological Research.” Psychological Methods 4 (3). American Psychological Association: 272.

Faullant, R., K. Matzler, and T. A. Mooradian. 2013. “The Thrill of Victory, the Agony of Defeat: Personality, Perceptions of Price (Un)fairness, Emotions, and Price Satisfaction.” In Handbook of Psychology of Emotions: Recent Theoretical Perspectives and Novel Empirical Findings, 2:127–40. Nova Science Publishers, Inc.

Ferguson, Jodie L., Pam Scholder Ellen, and William O. Bearden. 2014. “Procedural and Distributive Fairness: Determinants of Overall Price Fairness.” Journal of Business Ethics: JBE 121 (2). Springer Netherlands: 217–31.

Frisou, Jean, and Hélène Yildiz. 2011. “Consumer Learning as a Determinant of a Multi-Partner Loyalty Program’s Effectiveness: A Behaviorist and Long-Term Perspective.” Journal of Retailing and Consumer Services 18 (1). Elsevier: 81–91.

Garbarino, Ellen, and Olivia F. Lee. 2003. “Dynamic Pricing in Internet Retail: Effects on Consumer Trust.” Psychology and Marketing 20 (6). Wiley Subscription Services, Inc., A Wiley Company: 495–513.

Goldman, B., and R. Cropanzano. 2015. “‘Justice’ and ‘fairness’ Are Not the Same Thing.” Journal of Organizational Behavior. Wiley Online Library. http://onlinelibrary.wiley.com/doi/10.1002/job.1956/full.

Gourville, John T., and Dilip Soman. 2011. “The Consumer Psychology of Mail-in Rebates.” Journal of Product & Brand Management 20 (2): 147–57.

Grewal, D., D. M. Hardesty, and G. R. Iyer. 2004. “The Effects of Buyer Identification and Purchase Timing on Consumers’ Perceptions of Trust, Price Fairness, and Repurchase Intentions.” Journal of Interactive Marketing 18 (4): 87–100.

Han, Seunghee, Jennifer S. Lerner, and Dacher Keltner. 2007. “Feelings and Consumer Decision Making: The Appraisal-Tendency Framework.” Journal of Consumer Psychology: The Official Journal of the Society for Consumer Psychology 17 (3): 158–68.

Haws, K. L., and W. O. Bearden. 2006. “Dynamic Pricing and Consumer Fairness Perceptions.” The Journal of Consumer Research 33 (3): 304–11.

Herrmann, Andreas, Lan Xia, Kent B. Monroe, and Frank Huber. 2007. “The Influence of Price Fairness on Customer Satisfaction: An Empirical Test in the Context of Automobile Purchases.” Journal of Product & Brand Management 16 (1): 49–58.

Hinz, O., I-H Hann, and M. Spann. 2011. “Price Discrimination in E-Commerce? An Examination of Dynamic Pricing in Name-Your-Own Price Markets.” MIS Quarterly: Management Information Systems 35 (1): 81–98.

Ho, Daniel, Kosuke Imai, Gary King, and Elizabeth Stuart. 2011. “MatchIt: Nonparametric Preprocessing for Parametric Causal Inference.” Journal of Statistical Software 42 (1): 1–28.

Hollensbe, E. C., S. Khazanchi, and S. S. Masterson. 2008. “How Do I Assess If My Supervisor and Organization Are Fair? Identifying the Rules Underlying Entity-Based Justice Perceptions.” Academy of Management Journal. Academy of Management 51 (6): 1099–1116.

Hu, Li-tze, and Peter M. Bentler. 1999. “Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives.” Structural Equation Modeling: A Multidisciplinary Journal 6 (1). Taylor & Francis: 1–55.

Izard, C. E., D. Z. Libero, P. Putnam, and O. M. Haynes. 1993. “Stability of Emotion Experiences and Their Relations to Traits of Personality.” Journal of Personality and Social Psychology 64 (5): 847–60.

Jin Seok Pyone, and Alice M. Isen. 2011. “Positive Affect, Intertemporal Choice, and

Levels of Thinking: Increasing Consumers' Willingness to Wait." JMR, Journal of Marketing Research 48 (3). journals.ama.org: 532–43.

Jones, David A., and Martin L. Martens. 2009. "The Mediating Role of Overall Fairness and the Moderating Role of Trust Certainty in Justice–criteria Relationships: The Formation and Use of Fairness Heuristics in the Workplace." Journal of Organizational Behavior 30 (8). John Wiley & Sons, Ltd.: 1025–51.

Kahneman, Daniel, Jack L. Knetsch, and Richard H. Thaler. 1986. "Fairness and the Assumptions of Economics." The Journal of Business 59 (4). University of Chicago Press: S285–300.

Kannan, P. K., and P. K. Kopalle. 2001. "Dynamic Pricing on the Internet: Importance and Implications for Consumer Behavior." International Journal of Electronic Commerce 5 (3): 63–83.

Kaptein, Maurits, and Petri Parvinen. 2015. "Sequential Learning Of Profit Maximizing Sales Prices." In Marketing Dynamism & Sustainability: Things Change, Things Stay the Same…, edited by Leroy Robinson Jr., 398–401. Developments in Marketing Science: Proceedings of the Academy of Marketing Science. Springer International Publishing.

Keltner, D., & Lerner, J. S. (2010). Emotion. In Handbook of Social Psychology. John Wiley & Sons, Inc.

Kimes, Sheryl E. 1994. "Perceived Fairness of Yield Management." The Cornell Hotel and Restaurant Administration Quarterly 35 (1). Elsevier: 22–29.

Kim, Hyeong Min. 2006. "Consumers' Responses to Price Presentation Formats in Rebate Advertisements." Journal of Retailing 82 (4): 309–17.

Kukar-Kinney, Monika, Lan Xia, and Kent B. Monroe. 2007. "Consumers' Perceptions of the Fairness of Price-Matching Refund Policies." Journal of Retailing 83 (3). Elsevier: 325–37.

Lal, Rajiv, and David E. Bell. 2003. "The Impact of Frequent Shopper Programs in Grocery Retailing." Quantitative Marketing and Economics 1 (2). Kluwer Academic Publishers: 179–202.

Lee, S., A. Illia, and A. Lawson-Body. 2011. "Perceived Price Fairness of Dynamic Pricing." Industrial Management and Data Systems 111 (4): 531–50.

Lerner, Jennifer S., and Dacher Keltner. 2000. “Beyond Valence: Toward a Model of Emotion-Specific Influences on Judgement and Choice.” Cognition and Emotion 14 (4). Taylor & Francis: 473–93.

Lerner, J. S., Y. Li, P. Valdesolo, and K. S. Kassam. 2015. “Emotion and Decision Making.” In Annual Review of Psychology, 66:799–823. Annual Reviews Inc.

Leventhal, Gerald S. 1980. “What Should Be Done with Equity Theory?” In Social Exchange, 27–55. Springer.

Lind, E. Allan. 2001. “Fairness Heuristic Theory: Justice Judgments as Pivotal Cognitions in Organizational Relations.” In Advances in Organizational Justice, edited by J. Greenberg and Russell Cropanzano. Vol. 56.

Liu, Yuping. 2007. “The Long-Term Impact of Loyalty Programs on Consumer Purchase Behavior and Loyalty.” Journal of Marketing 71 (4): 19–35.

Lu, Qiang, and Sridhar Moorthy. 2007. “Coupons Versus Rebates.” Marketing Science 26 (1). pubsonline.informs.org: 67–82.

Matute-Vallejo, Jorge, Rafael Bravo, and José M. Pina. 2011. “The Influence of Corporate Social Responsibility and Price Fairness on Customer Behaviour: Evidence from the Financial Sector.” Corporate Social Responsibility and Environmental Management 18 (6). John Wiley & Sons, Ltd.: 317–31.

Maxwell, Sarah, and Lucette Comer. 2010. “The Two Components of a Fair Price: Social and Personal.” Journal of Product & Brand Management 19 (5): 375–80.

Maxwell, S., and E. Garbarino. 2010. “The Identification of Social Norms of Price Discrimination on the Internet.” Journal of Product and Brand Management 19 (3): 218–24.

McCall, Michael, Carol L. Bruneau, Aimee Dars Ellis, and Kimberly Mian. 2009. “A Framework for Understanding Consumptive Delay: Rebate Proneness and Redemption.” Journal of Product & Brand Management 18 (6): 461–67.

Mikula, G., and K. R. Scherer. 1998. “The Role of Injustice in the Elicitation of Differential Emotional Reactions.” Personality and Social Psychology Review: An Official Journal of the Society for Personality and Social Psychology, Inc. psp.sagepub.com. http://psp.sagepub.com/content/24/7/769.short.

Mullen, Elizabeth. 2007. “The Reciprocal Relationship between Affect and Perceptions of Fairness.” Distributive and Procedural Justice: Research and Social Applications. Ashgate Publishing Company Hampshire,, England, 15–37.

Noordhoff, Corine, Pieter Pauwels, and Gaby Odekerken-Schröder. 2004. “The Effect of Customer Card Programs: A Comparative Study in Singapore and The Netherlands.” International Journal of Service Industry Management 15 (4). emeraldinsight.com: 351–64.

Parasuraman, Ananthanarayanan, Valarie A. Zeithaml, and Arvind Malhotra. 2005. “ES-QUAL a Multiple-Item Scale for Assessing Electronic Service Quality.” Journal of Service Research 7 (3). SAGE Publications: 213–33.

Pham, Michel Tuan. 2007. “Emotion and Rationality: A Critical Review and Interpretation of Empirical Evidence.” Review of General Psychology: Journal of Division 1, of the American Psychological Association 11 (2). Educational Publishing Foundation: 155.

Pornprasertmanit, Sunthud, Patrick Miller, Alexander Schoemann, Yves Rosseel, C. Quick, M. Garnier-Villarreal, and Others. 2013. “semTools: Useful Tools for Structural Equation Modeling.. R Package Version 0.4-14.” Retrieved July 17: 2013.

Randolph, Justus J., Kristina Falbe, Austin Kureethara Manuel, and Joseph L. Balloun. 2014. “A Step-by-Step Guide to Propensity Score Matching in R.” Practical Assessment, Research & Evaluation 19 (18). Dr. Lawrence M. Rudner: 2.

Raykov, T. 2001. “Estimation of Congeneric Scale Reliability Using Covariance Structure Analysis with Nonlinear Constraints.” The British Journal of Mathematical and Statistical Psychology 54 (Pt 2): 315–23.

R Core Team. 2016. “R: A Language and Environment for Statistical Computing.” Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Revelle, W. 2016. “Psych: Procedures for Personality and Psychological Research, Northwestern University, Evanston, Illinois, USA, Version=1.6.12.”

Rosseel, Yves. 2012. “Lavaan: An R Package for Structural Equation Modeling.” Journal of Statistical Software 48 (1): 1–36.

RStudio Team. 2016. “RStudio: Integrated Development Environment for R.” Boston, MA: RStudio, Inc. http://www.rstudio.com/.

Satorra, Albert, and Peter M. Bentler. 2010. “Ensuring Positiveness of the Scaled Difference Chi-Square Test Statistic.” Psychometrika 75 (2). Springer: 243–48.

Schoefer, Klaus, and Adamantios Diamantopoulos. 2008. “The Role of Emotions in Translating Perceptions of (In)Justice into Postcomplaint Behavioral Responses.” Journal of Service Research 11 (1): 91–103.

Schweitzer, M. E., and D. E. Gibson. 2008. “Fairness, Feelings, and Ethical Decision-Making: Consequences of Violating Community Standards of Fairness.” Journal of Business Ethics: JBE 77 (3): 287–301.

Skarlicki, D. P., R. Folger, and P. Tesluk. 1999. “Personality as a Moderator in the Relationship between Fairness and Retaliation.” Academy of Management Journal. Academy of Management 42 (1): 100–108.

Vaidyanathan, Rajiv, and Praveen Aggarwal. 2003. “Who Is the Fairest of Them All? An Attributional Approach to Price Fairness Perceptions.” Journal of Business Research 56 (6): 453–63.

Watson, D., and L. A. Clark. 1999. “The PANAS-X: Manual for the Positive and Negative Affect Schedule-Expanded Form.” ir.uiowa.edu. http://ir.uiowa.edu/cgi/viewcontent.cgi?article=1011&context=psychology_pubs.

Weidman, Aaron C., Conor M. Steckler, and Jessica L. Tracy. 2017. “The Jingle and Jangle of Emotion Assessment: Imprecise Measurement, Casual Scale Usage, and Conceptual Fuzziness in Emotion Research.” Emotion 17 (2): 267–95.

Weiss, Howard M., Kathleen Suckow, and Russell Cropanzano. 1999. “Effects of Justice Conditions on Discrete Emotions.” The Journal of Applied Psychology 84 (5). American Psychological Association: 786.

Widaman, Keith F., Emilio Ferrer, and Rand D. Conger. 2010. “Factorial Invariance within Longitudinal Structural Equation Models: Measuring the Same Construct across Time.” Child Development Perspectives 4 (1): 10–18.

Xia, Lan, Monika Kukar-Kinney, and Kent B. Monroe. 2010. “Effects of Consumers’ Efforts on Price and Promotion Fairness Perceptions.” Journal of Retailing 86 (1): 1–10.

Xia, Lan, Kent B. Monroe, and Jennifer L. Cox. 2004. “The Price Is Unfair! A Conceptual Framework of Price Fairness Perceptions.” Journal of Marketing 68 (4). American

Marketing Association: 1–15.

Yang-Wallentin, Fan, Karl G. Jöreskog, and Hao Luo. 2010. “Confirmatory Factor Analysis of Ordinal Variables With Misspecified Models.” Structural Equation Modeling: A Multidisciplinary Journal 17 (3): 392–423.

Yu, Ching-Yun. 2002. “Evaluating Cutoff Criteria of Model Fit Indices for Latent Variable Models with Binary and Continuous Outcomes.” University of California Los Angeles. http://ww.statmodel2.com/download/Yudissertation.pdf.

Zeithaml, Valarie A., Leonard L. Berry, and A. Parasuraman. 1996. “The Behavioral Consequences of Service Quality.” Journal of Marketing 60 (2). American Marketing Association: 31–46.

Appendices

Appendix A - Full manipulation texts in Finnish

Text for second group:
[Yrityksen nimi] järjestelmissä on nyt meneillään kokeilu, jossa osalle asiakkaista näytettävät hyvitysprosentit ovat edelleen ihmisen määräämiä ja osan määrittelee algoritmi, joka muokkaa hyvitysprosentin tasoa eri näyttökertojen välillä.

[Questions on belonging to the group & Gain/loss]

Text for third group:
[Yrityksen nimi] järjestelmissä on nyt meneillään kokeilu, jossa osalle asiakkaista näytettävät hyvitysprosentit ovat edelleen ihmisen määräämiä ja osan määrittelee algoritmi, joka muokkaa hyvitysprosentin tasoa eri näyttökertojen välillä.

Algoritmi toimii siten, että alkuvaiheessa se esittää eri käyttäjille satunnaisesti luotuja hyvitysprosentteja ennakkoon asetetuissa raameissa. Myöhemmin asiakkaiden klikkauksien kautta saadun palautteen perusteella algoritmi etsii hyvitysprosentin optimaalisen tason. Tämä tarkoittaa, että eri aikana vierailleet ihmiset saattavat saada erilaisen hyvitysprosentin. Algoritmi käyttää ryhmätasoista tietoa, eikä käytä asiakkaiden yksilöityä ostohistoriaa hyvitysprosentin määrittämiseksi.

[Questions on belonging to the group & Gain/loss]

[PAGE BREAK]

[Osa näkemistäsi hyvitysprosenteista oli algoritmin määrittämiä.]
OR
[Näit vain ihmisen määräämät hyvitysprosentit, eli et ole altistunut algoritmin tuottamille hyvitysprosenteille.]

Appendix B - Finnish fairness measures used in research

All questions measured on likert: 1 täysin eri mieltä - 5 täysin samaa mieltä

Event fairness:

Distributive scale:

FD1: Näkemäni hyvitysprosentti on reilu?

FD2: Näkemäni hyvitysprosentti on perusteltu?

FD3: Näkemäni hyvitysprosentti on hyväksyttävä?

FD4: Näkemäni hyvitysprosentti on tasapainossa vaivannäköni kanssa?

Procedural scale:

FP1: Hyvitysprosentin määrittelytapa on ymmärrettävä?

FP2: Hyvitysprosentin määrittelytapa on säännönmukainen?

FP3: Hyvitysprosentin määrittelytapa kohtelee kaikkia asiakkaita samalla tavoin?

Entity fairness:

FE1: [Yrityksen nimi] yleensä kohtelee minua oikeudenmukaisesti

FE2: [Yrityksen nimi] on reilu yritys

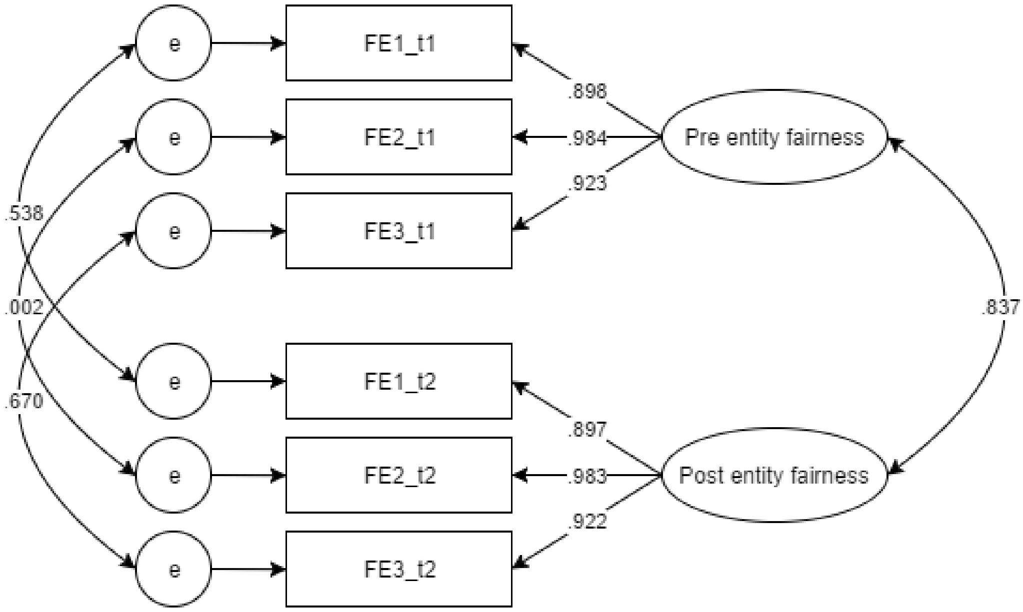
FE3: Oikeudenmukainen on sopiva sana kuvaamaan [Yrityksen nimi]

Appendix C - Event fairness EFA item loading matrix

	Distributive	Procedural	Communality
FD1	**.82**	.08	.78
FD2	**.58**	**.31**	.69
FD3	**.97**	-.11	.80
FD4	**.76**	.10	.70
FP1	-.01	**.86**	.74
FP2	.00	**.92**	.84
FP3	.15	**.63**	.55

Note: Bold remarks are loadings allowed in adjusted CFA model

Appendix D - Pre and post entity fairness measurement strong time invariant measurement model



Fit indices of the model (χ^2[3, N = 559] = 6.93, p = .074, CFI = 1.000, RMSEA = .048, SRMR = .007, WRMR = .323).

Note. Standardized solution presented. All covariances and loadings are significant at level p<.001, except for covariance of item FE2, which is not significant. e = measurement error.

Appendix F – Results of time invariance tests for DES-IV scales

Interest:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale.f
1	0	0	0,065	0,009	0,198	2,32	3	0,509	0,519
1	0	0	0,054	0,011	0,283	4,246	5	0,515	0,728
1	0	0	0,066	0,011	0,283	2,416	3	0,491	0,94

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=1.526$, p=0.466
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Enjoyment:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale.f
0,992	0,172	0,133	0,215	0,034	0,847	52,743	3	0	0,525
0,991	0,136	0,105	0,169	0,045	1,032	56,294	5	0	0,74
0,993	0,154	0,115	0,197	0,045	1,032	42,732	3	0	0,955

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=12.676$, p=0.002
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Surprise:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
0,999	0,049	0	0,097	0,016	0,317	7,034	3	0,071	0,512
0,998	0,052	0,015	0,089	0,021	0,486	12,50	5	0,029	0,746
0,999	0,059	0,015	0,106	0,021	0,486	8,81	3	0,032	0,963

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=4.86$, p=0.088
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Sadness:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale.f
1	0	0	0,061	0,008	0,169	2,006	3	0,571	0,428
1	0	0	0,044	0,01	0,216	2,972	5	0,704	0,601
1	0	0	0,053	0,01	0,216	1,429	3	0,699	0,775

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=0.823$, p=0.663
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Anger:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale.f
1	0,027	0	0,081	0,015	0,258	4,216	3	0,239	0,547
1	0	0	0,054	0,016	0,263	4,286	5	0,509	0,593
1	0	0	0,066	0,016	0,263	2,447	3	0,485	0,765

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=0.129$, $p=0.938$
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, $p=1$

Disgust:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
1	0,006	0	0,072	0,015	0,237	3,062	3	0,382	0,656
0,999	0,038	0	0,077	0,026	0,471	9,028	5	0,108	0,94
0,999	0,043	0	0,093	0,026	0,471	6,12	3	0,106	1,213

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=4.418$, $p=0.11$
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, $p=1$

Contempt:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
0,999	0,035	0	0,086	0,018	0,27	5,024	3	0,17	0,543
0,999	0,023	0	0,067	0,021	0,327	6,491	5	0,261	0,634
1	0,026	0	0,08	0,021	0,327	4,155	3	0,245	0,819

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=1.694$, $p=0.429$
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, $p=1$

Fear:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
0,999	0,043	0	0,092	0,019	0,318	6,095	3	0,107	0,589
1	0,019	0	0,064	0,019	0,322	6,016	5	0,305	0,636
1	0,022	0	0,078	0,019	0,322	3,787	3	0,285	0,821

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=0.107$, $p=0.948$
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, $p=1$

Guilt:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
1	0	0	0,043	0,006	0,132	0,919	3	0,821	0,444
0,996	0,082	0,051	0,117	0,029	0,614	23,95	5	0	0,612
0,997	0,094	0,055	0,138	0,029	0,614	17,68	3	0,001	0,791

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=16.154$, p=0
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Shame:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
1	0	0	0,062	0,011	0,195	2,073	3	0,557	0,614
0,999	0,041	0	0,079	0,024	0,42	9,677	5	0,085	0,712
0,999	0,047	0	0,095	0,024	0,42	6,623	3	0,085	0,919

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=6.216$, p=0.045
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Shyness:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
0,999	0,045	0	0,094	0,016	0,287	6,42	3	0,093	0,461
0,998	0,047	0,002	0,084	0,024	0,419	11,10	5	0,049	0,614
0,999	0,053	0	0,101	0,024	0,419	7,73	3	0,052	0,793

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=4.287$, p=0.117
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Hostility inwards:

cfi	rmsea	rmsea.ci.l	rmsea.ci.u	srmr	wrmr	chisq	df	p	chisq.scale
1	0,028	0	0,082	0,011	0,239	4,36	3	0,225	0,457
0,999	0,057	0,023	0,094	0,02	0,503	14,16	5	0,015	0,704
0,999	0,065	0,024	0,111	0,02	0,503	10,09	3	0,018	0,909

Satorra&Bentler-test, configural vs. weak: $\chi^2(2)=7.084$, p=0.029
Satorra&Bentler-test, weak vs. strong: $\chi^2(2)=0$, p=1

Appendix F - Behavioral intentions: original and adjusted model EFA item loading matrix

Original model:

	F1	F2	F3	F4	Communality
BI1	**.97**	.00	-.03	-.03	.88
BI2	**.79**	-.03	-.04	*.26*	.88
BI3	**.85**	.02	.12	-.10	.76
BI4	**.21**	-.11	.19	*.60*	.75
BI5	.02	.03	**.98**	.00	.97
BI6	.02	*.27*	**-.51**	-.11	.43
BI7	-.02	**.76**	.01	.06	.57
BI8	.01	**.94**	.00	-.04	.90
BI9	.00	*.36*	.05	**.38**	.23

Note: Bold remarks are loadings corresponding to Zeithaml et al. (1996) factor structure, italic remarks are for major (>.20) crossloading other factors.
F1 - Loyalty, F2 - External response, F3 - Switch scale, F4 - Internal response

Adjusted model:

	F1	F2	F3	Communality
BI1	**.94**	.04	-.03	.84
BI2	**.96**	-.04	-.05	.87
BI3	**.79**	.07	.11	.73
BI4	**.56**	**-.20**	**.18**	.56
BI5	.01	.04	**1.00**	1.00
BI6	-.05	**.30**	**-.50**	.42
BI7	.03	**.76**	.02	.57
BI8	-.01	**.93**	.00	.87

Note: Bold remarks are loadings allowed in adjusted CFA model
F1 - Recommendation, F2 - Complaining, F3 - Coming back